ONLINE SOCIAL MEDIA AS A SOCIAL-ECOLOGICAL SYSTEMS RESEARCH TOOL: FACEBOOK AND TWO RURAL ALASKAN COMMUNITIES

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Abstract

The earth has transitioned into the anthropocene, which is defined by complex environmental change linked to human behavior and requires new tools of analysis in order to understand shifting social-ecological system (SES) dynamics. In this work, I explore taking advantage of widespread online social media participation to develop the tools for doing so. Spatially grounded public exchanges on Facebook are examined with three goals in mind: 1) examine the types of SES content being passed through this communication medium, 2) compare community observations to relevant scientific observations, and 3) define a flexible and reproducible research method for integrating these communications signals into a wide range of SES studies. Facebook activity from two communities in northwest Alaska was studied. Communication patterns were assessed combining content and network analysis methodology. My results indicate that signals are passed through this mode of communication directly addressing the SES topics of subsistence, food security, and human-weather interactions. Data from instrumentally based weather observations are qualitatively aligned with posting frequency and content. A context and community-based research method is defined that uses staged deductive/inductive content analysis, in conjunction with network analysis, to identify emergent local SES relationships.

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General Introduction

The ongoing transition into the anthropocene (Crutzen, 2006) is characterized by increased rates of environmental change linked to human global behavior. Increased storm size and intensity, drought, desertification, persistent environmental pollutants, heat-waves, ocean acidification, and the disappearance of arctic sea ice are all indicators of environmental changes that have global causes and local effects (Steffen et al., 2004). Manifestations of these effects are increasingly interfering with the day-to-day life patterns of Arctic residents. However, these impacts are geographically variable and create unique issues for each community they affect, based on diverse social and ecological relationships (Chapin et al., 2006). There is a growing recognition in the Western scientific community that to address these environmental issues an integrated approach must be devised that considers social feedback mechanisms through a joint social and ecological framework capable of reacting to local and regional variability (Folke, 2006). New tools of analysis that explore linkages between social and ecological systems are required to understand, prepare for, and respond to the novel challenges created by increased coupling of these two systems.

Simultaneous to the increased coupling of global social and ecological systems, new-media communication tools, from mobile to internet technologies, are rapidly changing how people interact with one another (Haythornthwaite, 2002). This is occurring at a range of communication scales from the interpersonal to broadcast and is reshaping the geographic and social network boundaries that aid in defining each individual's worldview (Hampton, Goulet, Rainie, & Purcell, 2011). Additionally, new media tools are redefining concepts of public and private space and increasing access for researchers, resource managers, policymakers, and planners alike to how people understand the social-ecological systems (SESs) they live in. The difficulty arises in filtering through the vast volumes of data produced via new media to derive meaningful, place-based information that is relevant to a wide variety of stakeholders and decision-makers tasked with addressing novel challenges of the anthropocene. I use social media generated data, specifically derived from the website Facebook, to develop a tool for doing so.

Study Rationale

Social understanding and action is intricately linked to a society's communication practices (Jonassen, Davidson, Collins, Campbell, & Haag, 1995). The act of passing information between one individual and the next, regardless of the mode of transfer, is the fundamental mechanism by which individuals can combine to form collectives (Backstrom, Huttenlocher, Kleinberg, & Lan, 2006). Collective human action, planned or otherwise, is in turn, the mechanism through which humanity developed the ability to enter the anthropocene in the first place and is the only recognizable mechanism through which humanity can adapt to the demands of it. A defining consequence of the anthropocene is that local actions and decisions can impact social-ecological systems at scales beyond the scope of local observation (Chapin, Kofinas, Folke, & Chapin, 2009), and at rates outside that of historical human experience. Adaptation to the new realities and responsibilities of these characteristics of the anthropocene, societal communication practices must evolve to span these challenges. The premise of this work is that the creation of large social networks, which are effective at quickly conveying highly localized and accurate observations to distant and diverse populations are a fundamental requirement in meeting these challenges. Social media, here defined as online-based applications that allow for two-way communication between spatially, temporally, and culturally diverse participants is postulated as an evolving tool through which these types of networks can be developed and maintained. Given this set of presumptions, in this research I attempt to determine if SES indicators (formally defined during the "deductive" stage of my methods described below) are passed through locally grounded social media networks, and if so, are they reliably comparable to instrumental data, and lastly, can a rigorous and reproducible research method be devised to explore them?

Rural Alaska is a unique location to explore social media communication practices for SES indicators for three distinct reasons. First, Alaska is experiencing greater climate warming than many lower latitudes (Hinzman et al., 2005), with widespread environmental fluctuations. Second, communities in the region practice mixed cash and subsistence based economy (Callaway et al., 1999); resulting in populations that are out on the landscape regularly and are thus highly attuned to environmental changes that impact their day-to-day lives. And lastly, while the region is remote with sporadic infrastructural systems (Us Army Corps of Engineers, 2006), there is an extensive, modern, and growing telecommunication system in the region (Terra, 2010) that facilitates local social media use. These three factors combine to create an informed, well connected study population facing considerable SES challenges which are tied to a shared global driver (climate warming) with locally variable expressions and social impacts.

Study Context

Sustainability science is an attempt by Western academia, through an integrated approach, to tap into both the social and natural sciences in order to develop an understanding of the human role in the anthropocene (Folke, 2006). It is a recognition of the problems associated with this new phase in earth history and an awareness of the implications to a "Full World" where all natural resources are in use with little or no reserves, and where ecological tipping points are nearly reached, or in many cases already crossed at the local level (Costanza, 2008). The origins of this concept are derived from ecological studies and are based on a systems-thinking perspective. The critical concept is the idea of the social-ecological system (SES).

The main intent, and the working definition for this research, of the SES concept is to look at any specific issue or environmental challenge from a systems perspective involving environmental and social factors interacting at multiple spatial and temporal scales (Chapin et al., 2006). Critical to this form of understanding is that there are both social and environmental processes occurring outside the immediate boundaries of the challenge at hand, exogenous effects, and that there are also both fast and slow variables affecting the system directly. All of these factors interact, but the blending of social and environmental factors is an important new step in traditional Western science. Positively resolving whatever issue is at hand, and typically this requires some form of adaptation, coping, or transformation process to occur, is highly dependent on identifying the system components and their interconnections in order to drive change in a controlled fashion. Without doing so, change will still occur, it simply may not be desirable to the human actors involved. The primary argument of this work is that social media, specifically Facebook, can offer insight into identifying relevant system components (as well as actors) across scales. What exactly is considered a "relevant system component" is context and research dependent. In the case studies of this work, relevant components are defined through the deductive and inductive coding process discussed below and based on Facebook conversations around subsistence, food, and weather topics.

Geographic Scope

I look at two communities in northwestern Alaska (figure. I.1) in detail. Generally, communities in the region can be classified into two basic categories, hub and village, defined by the population size and services available in each. Hub communities typically have populations of a few thousand residents while villages are 1-2 orders of magnitude less. Services that can be found in villages are limited. Typically a small health clinic, school, post office, airfield, city and tribal office, small power plant, fuel station and tank farm, and a small general store. Villages often do not have individual home-serviced municipal water or sewer systems and are rarely interconnected via road systems. Single-engine aircraft are the primary method of travel into and out of most villages in Alaska. Hub communities, on the other hand, have greater service options; larger stores, small hospitals, more developed shipping infrastructure (though still very limited by most modern standards), and commercial jet air service. Hubs connect the villages of rural Alaska to the urban centers of the state, as well as to larger shipping ports along the west coast of the US via ocean and river going barges. Most villages depend upon a single hub to reach more urbanized areas and are separated from one another by considerable spatial distances, though considerably less social distance. The location of hub communities is closely connected to traditional cultural territories and geophysical characteristics. The individual networks of hub communities and their satellite villages are the premise for regional classification in this study and represent only one possible method for defining internal regions within Alaska.

Sources of Evidence

I use content from the social media platform Facebook as the primary source of evidence in this work. Specifically, text-based content of publicly available postings are examined for all users who self-identify with either of the two case study communities as their place of residence in their Facebook profiles. Individuals who do not specifically identify the current place of residence or have non-public profiles are not included in the study.

To define whether or not SES relevant content is being shared through this medium, a deductive framework of four broad content categories are used to identify likely SES indicators within the study population. These are weather, food, gathering, and hunting. A miscellaneous category, environment, is also used to account for human-environmental interaction content that does not cleanly fit into the primary categories but never the less shares information regarding direct human/environment interactions. Examples of the type of content identified using this method can be seen in table I.1. The date and location of each post fitting these criteria are recorded. As is the social network of users who interacted with the content, either through “liking” or “commenting” on the post.

Considering the information gained through social media monitoring as a practical tool for SES research, it is fundamentally important to assess how the lived experience of human-environment interactions conveyed through the media compares to concurrent instrumental observations of environmental conditions. This is addressed by comparing social media derived weather observations with National Weather Service records for temperature, wind, and precipitation.

Methods of Analysis

The development of a methodological template specific to SESs is a prime concern for me in this study. The template must be capable of 1) addressing a range of SES relevant questions not specific to the case studies used in this work, and 2) be sufficiently flexible to adapt to changing SES and social media conditions. A procedural order is developed to address these requirements by blending content and network analysis techniques.

The first step, via content analysis, uses a deductive framework derived from established regional and globally scaled SES research to search for and identify relevant, locally placed social media content. This is accomplished by using the regionally identified SES concern over climate interactions with subsistence life-ways to develop the weather, food, gather, hunt, and environment framework discussed above. The “find friends” feature of Facebook, used with the “current city” filter next allows data to be locally placed. Through this method a census of all publicly identifiable Facebook users from each of the study sites is identified. This step can be mimicked in most social media applications by using their respective built-in network building tools, thus meeting the methodological platform flexibility requirements. All public content from this sample base is scanned for communication related to the deductive framework. The next step of analysis is to develop more detailed SES themes within the deductive framework via a grounded, inductive, coding process. This study tracked relevant content for a six-month period from August 2012 to January 2013. The relationship networks surrounding this content and those who “liked” or “commented” on it are generated. This creates a series of spatially and temporally linked networks that are first degree representations of life-experience based SES information conveyed via public social media communication channels.

These networks are multi-scaled. Their origins are place-based and representative of traditional physical community boundaries- i.e. by methodological consequence, as the networks are developed from users self-identifying with the physical spaces (villages) in which they live. However, as the networks grow through identification of deductive and grounded coding relationships, and the individual person-to-person ties that evolve around these relationships, content-based virtual communities emerge. The virtual communities, while heavily linked to physical space through legacy networks not examined in this study (friendship, family, sharing, etc.) are not limited by physical proximity, but rather social proximity as derived from a hybrid face-to-face and new media communication ecology that they are participating in. The decoupling of a rich communication experience from local-space to virtual-space potentially expands the SES reference frame beyond that of the locally observable and allows for historically understood local-level awareness, via interpersonal communication, to incorporate regional-level awareness. This is seen as a positive feedback input in a larger system defining the on going regionally based social response to erratic and often dramatic ecological fluctuations.

This study depends heavily upon the use of social network analysis (SNA) as a means of understanding the SES information conveyed through Facebook. Limited research has thus far been conducted to examine the specific network principles involved in SES issues (Bodin, & Prell, 2011). This is not true for other disciplines however, and SNA, particularly in the fields of corporate management, health care, and state security is a rapidly expanding avenue of research with a rich and growing body of theory to support it (Borgatti, Mehra, Brass, & Labianca, 2009). SES investigations, and more broadly speaking the entire field of sustainability science, can benefit from the methodological inclusion of SNA (Bodin, & Prell, 2011).

Social networks are constructed of nodes and ties. In this study nodes are required to be SES elements, which include individuals as well as ecological components. Ties represent context-based social connections between nodes. The social network is then delineated by the relative location of nodes to one another as defined by the ties connecting them. Three basic network principals are valuable to review at present, with more detailed theoretical and analytical explanations to follow as warranted in the remaining chapters of this thesis. Fundamental concepts to understand are ideas on “bonding” and “bridging” structures, as well as the analytical concept of node centrality (Borgatti & Halgin, 2011; Granovetter, 1973). All three are concerned with the relationships between nodes in a network, rather than a primary focus on node properties.

Bonding structures refer to networks where a set of nodes shares many ties among themselves. This is common in family groups or close circles of friends where any given person in the group is likely to know all, or most, others in the group (figure I.2). These types of networks are associated with the ability to provide strong emotional support to individuals within the group. However, they lack the ability to introduce new resources (knowledge, material, or opportunity) into the network. This is because any resource node A has access to, node B (or C, or D) is likely to have access to as well through another connection in the network. Through this type of network structure, there is limited opportunity for new resources to enter (Borgatti & Halgin, 2011).

The introduction of new resources into a network, therefore, is more strongly associated with bridging structures (Granovetter, 1973). This is a situation where two bonded groups are connected by just one or two ties (figure I.3). This makes intuitive sense, in that through the bridging structure group 1 in figure I.3 has potential access to the resources of group 2, and vise versa.

Node centrality refers to the structural position of a given node within a larger network. This can be measured in a variety of ways, the most basic being “degree” which records the number of ties that connect the node to the rest of the network (figure. I.4). Using degree, a more central node will have a greater number of ties connecting it to the network. Controlled experimentation (Bavelas, 1950) has shown that centralized nodes hold the greatest influence on a given network. Given this, centrality is a key measure in many network analysis studies.

Social network theory has built from recognition of these few basic types of network structures and measures into a complex and rich academic discipline of its own value. Social network analysis then describes a suite of quantitative tools used to explore social network theory and is grounded in principles of linear algebra. Essentially, a network can be represented as a mathematical matrix where the column and row headings reference individual nodes and the internal body of the matrix is filled with information that describes the ties shared between nodes (Borgatti, Everett & Johnson, 2013). These are often simply represented by a 0 or 1 to indicate the presence or absence of a tie, but may also utilize a range of numerical values to indicate various aspects of different tie strengths and relationships (Borgatti, Everett & Johnson, 2013). Once a network is conceptualized as a matrix, a variety of calculations can be performed to analyze relationships within it. The usefulness of this form of conceptualization is that analysis can be performed at a wide range of network scales, based on research need, from individual node to whole network characterizations.

Explicit in most modern conceptualizations of network theory is the concept that information, and depending on context, material goods, flows through ties to nodes. Thus, understanding network structure, and the implications of its various structural forms, is a critical step in understanding the access individuals within a given network have to information needed for knowledge construction and the material goods required to meet physical needs (Borgatti & Halgin, 2011).

Defining network boundaries is an important aspect to SNA. Two main types of networks are regularly defined and studied. The first is a "complete" (or "whole") network, and involves situations where all the members of a network can be readily identified and known. This is generally associated with organizational or workplace studies (Monge, & Contractor, 2003). Incomplete networks are much more common, and are representative of the type network studied in this work. They are characterized by an inability to be certain all members of a given network are accounted for in the data set.

As mentioned, the quantitative understanding of these structures is based on principles of linear algebra, specifically the mathematical construct of graph theory (Borgatti, Everett & Johnson, 2013) and not surprisingly the API used to develop the online social networking site Facebook is based on these same principles. This, in conjunction with the massive popularity of the website, over 50% of Americans are active Facebook users (Hampton, Goulet, Rainie & Purcell, 2011) with more than 800 million users world wide (Facebook, 2011), make it a prime location to study organically formed informal social networks and a prime place to search for otherwise hidden social connections useful to improved SES understanding.

Figures

Figure I.1. Field Map Illustrating Approximate Locations of Study Communities A and B. Map generated using the web-based mapping application Google Earth.

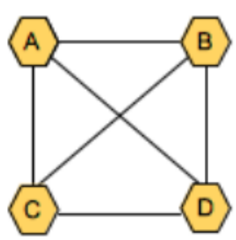

Figure I.2: Figure 2. Bonded Network (A tightly bonded network. Each node shares a tie with every other node.)

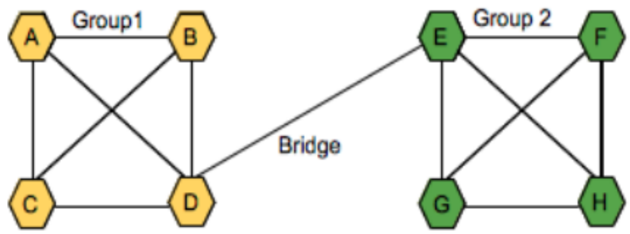

Figure I.3: Figure 3. Bridging Network (Groups 1 and 2 are tightly bonded internally. The tie between nodes D and E represents a bridging relationship. This connection allows group 1 potential access to the resources of group 2, and vice versa.)

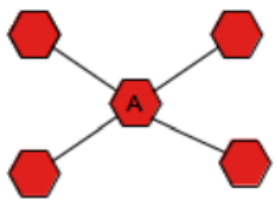

Figure I.4: Figure 4. Basic Centrality (Node A is most central as it has a tie to every other node. While the other nodes are less central, having ties only to A.)

Tables

Table I.1 Facebook Generated Content. Example of user generated content on the social media website Facebook.

User	Community	Post	Deductive Code	Date
76	B	It's snowing!	weather	October 28
6	B	Where's all the snow at? I wanna go slid! Lol	weather	October 28
59	A	yummy my moms bread is done... home made bread loafs..	food	October 29
33	B	It's snowing, it's snowing, the old women is snoring!!! YAY!!! About time :) gn	weather	October 29
42	B	I'm feeling a lil' left out this evening, Dun decided to go for a ride across airport lake and I had to stay to work. Oh, how I wish I were with him right now...	environment	October 30
27	B	Bin staying in to much needs to go out n have a good cold fresh air.,?!'	weather	October 30
29	A	yaay! Thanks to my wonderous boyfriend, i ordered my pop! coming in tomorrow suckkas! lol good evening frm a8! ran outa candies , time to relax while my girls are asleep! Gn... Love you babe♥♥ — with	food	October 31
68	A	anybody got white fish for dog food they wanna sell??	food	Wednesday (oct 31 2012)
98	A	Happy Halloween everybody dress warm.. pretty cold out today!!!	weather	October 31
103	B	well good day at work so far.. i think this day is going to go by fast like the wind outside.. lol	weather	October 31

Chapter 1:

Placing the Study Within the Context of Ongoing Academic Research

1.1 Introduction

My goal in this thesis is to develop a method for utilizing social media as a tool in understanding the social-ecological impacts of rapidly shifting environmental conditions. I use two communities in rural Alaska as case studies in this effort. This is a unique field location due to the combination of three factors. First, communities in the region are geographically dispersed and physically isolated (Us Army Corps of Engineers, 2006). However, they are connected via cultural and commercial ties, and through a growing network of information and communication technology (Terra, 2012). Second, the primarily indigenous residents of rural Alaska depend on a mixed subsistence and cash-based economy (Callaway et al., 1999). This has preserved a tight relationship between residents and their local environments. Third, the entire region is experiencing persistent and erratic environmental shifts forced by regional climate warming (Hinzman, et al, 2005).

These three factors lead me to believe the region is experiencing widespread climate driven social adaptation. I test, then, the idea that information on how residents are experiencing and coping with environmental change will be passed through regionally grounded, topic-defined, social media networks. I then explore methods for monitoring these networks for use in SES research. Accomplishment of these goals makes it important to first investigate more broadly the current state of academic understanding specific to Facebook use, social-ecological systems in Alaska, and traditional knowledge utilization within the context of Alaskan environmental scientific understanding.

Keeping within the broader network approach of this work, I use a network analysis approach to frame my perception of the current state of understanding surrounding these three bodies of knowledge. A unique network was constructed for each pool of knowledge and used to understand how my own interdisciplinary work draws from, and in the future can contribute to, more disciplinary research pursuits. Networks were bounded by results returned from select key-word searches limited to the online database Web of Knowledge. Cited sources for each returned result were then identified and used to create a two-mode network. Each two-mode network was analyzed for a suite of centrality measures and structural relationships. This information was used to identify key pieces of literature for further qualitative content analysis.

Explaining my findings, I first describe in greater detail the methodology used to define and analyze each network. I then describe the individual results for each network, including both network and content analysis. Finally, I conclude with a discussion on how these results inform the remainder of my thesis.

1.2 Network Development

All three networks were developed using the following methods with the intent to define a limited, yet representative body of literature for the spheres of knowledge discussed above. Situationally, the absence of information may be as telling as its presence. Known sources of relevant information that were not returned using this network development methodology will be discussed in the individual network results presented below.

The process for developing the network for each body of knowledge has two major steps. These steps correspond to the individual development of each mode in the two-mode network analysis. I discuss each of these in order below.

Defining the primary-mode network elements is the first step. Doing this requires a question be developed that defines each network respective to the pool of knowledge being investigated. Next, a set of salient search terms must be identified for each question. For this study, these terms were developed based on relevance to the defining question and the sample size of search results (too big required more selectivity in term selection, too small meant terms of more inclusivity). Searches were conducted using the Web of Knowledge (WoK) database. A final filtering of raw search results was conducted based on relevance to defining question. Search results were screened to achieve a sample size of approximately 50 for each defined pool of knowledge. This initial size boundary was determined in order to limit the eventual network size to manageable proportions once citations articles are added. These results represent the initial or primary mode of network entities assessed in the network analysis and are the network elements most relevant to my thesis work as they represent researcher efforts tightly related to my own.

The secondary-mode of network entities are easily defined as all cited references listed on WoK primary mode elements (in most cases scholarly articles, but not always). In terms of my MA work, this second mode of the network represents the literature body that researchers working on questions closely related to my own work are turning to for intellectual support.

Taken individually the bodies of knowledge illustrated in each of the two modes of the network represent two scales of information relevant to my thesis. The primary mode is very specific, or local to my research question(s), while the secondary is more general, or global to the question(s). Each is clearly linked through this form of network conceptualization, and together, the two provide an excellent framework for drawing resources into my own work.

1.3 Network Analysis

Each network was analyzed using the same basic procedures combining visualization and analytical techniques to determine a suite of important articles for qualitative content analysis. All network visualization and analysis was conducted using UCInet and Netdraw software packages. Each network was processed by first cleaning all pendant nodes from the graph and underlying matrixes. Next, centrality measures were calculated and the graph was re-visualized using a spring-embedded algorithm. Finally, select articles were identified for content analysis based on betweeness scores and structural position. Articles were classified into a discreet structural naming scheme to aid analysis. This methodology allows for an analytical framework to aid in understanding the thematic content of individual nodes (articles). There is a potential methodological bias in the order of these procedures that tends to influence content analysis toward “fitting into” the analytical framework. While recognized, for the purpose of this study this is an acceptable flaw.

Initial removal of pendant nodes in this type of two-mode network only affects secondary mode elements. Or in other words, secondary elements are the only network entities removed from analysis in this step. Sequence of analysis matters here, and this statement is not true if pendents are removed later in the analysis process. However, this is deemed a necessary and justifiable first step. The result is to clear the graphs of elements unique to each research effort represented in the primary nodes. As an example of why this step is needed, imagine a study on beluga whale populations that purports to utilize traditional knowledge in its methods. This study will clearly cite relevant traditional knowledge sources, but it will also have a number of references that pertain to research on marine mammal ecology. This second set of literature, while interesting, is not highly pertinent to my study questions. So continue to imagine that there is also a study on the effects of oil field exploration returned as a primary-mode network element. This study also uses traditional knowledge and will cite relevant sources, but will have references that are tied to developments in petroleum engineering and energy policy. Removing pendents as a first step broadly filters the reference network of these two articles and focuses the network onto the shared elements of both studies. In this example, traditional knowledge is the common element and so relevant sources to that topic remain in the network. It is after this initial cleaning step that empirical analysis of the newly filtered network is calculated. Some situations could be envisioned where a primary node would cite a unique and relevant source that no other primary node cited. This relevant data would be lost in the methods I use here. However, this scenario is probably rare enough to be discounted in this study.

Centrality measures are of greatest interest in this work as they are indicators of network influence and will help to identify key pieces of literature in each body of knowledge. Centrality measures broadly function by looking at the number of ties a node shares with the rest of the network. The most simplistic measure is degree. A node's degree is a basic count of all its ties to the other nodes around it. Degree, betweeness, closeness, and eigenvector were all calculated in this study.

The two-mode nature of this study requires thought when interpreting these results, however. This is complicated by the fact that while in most two-mode networks ties within modes (i.e. primary-mode to secondary-mode) cannot exist, in this case they can (i.e. a primary article may cite another primary article). This creates a hybrid network form where analytical routines designed for one-mode networks are not a clean fit, yet, neither are methods designed specifically for two-mode networks.

Given this situation, the underlying motive behind each measure must be explored to determine which method is most appropriate to the situation. To that end, one-mode analytics have been show to be effective measures for two-mode data (Borgatti, 2010). Betweeness is a measure that explores the relationship a node has to pairs of nodes across the network. Therefore, the betweeness measure is testing the relative importance of a node in connecting pairs of nodes across the network (Borgatti & Everett, 1997; Hanneman & Riddle, 2005). It is a measure that indicates how important a node is in making connections between its neighbors. In networks developed for this study then, the betweeness score for a primary mode article will flux dependent on the structural position of the secondary mode references it cited. If cited references have a high-degree structural position then the betweeness score of the primary mode article increases. This method weights the quality of a node's connections rather than quantity in drawing or disseminating information across a network. Primary nodes are biased in this measure by allowing the possibility that they may be connected to each other while secondary nodes may never connect to one another. This is deemed reasonable based on the idea that the primary nodes are, by definition, the most relevant aspects of the network in addressing the research questions. This methodology biases results toward highlighting the relative importance of these nodes across the network.

Visualization of the network was achieved using a standard “spring-embedded” algorithm. This method places network nodes and ties on a two-dimensional, geodesic, coordinate system. Geodesic distances are measured as steps between nodes in a network and not distance across space. Therefore, two nodes directly connected would have a distance of 1, while two nodes that had to step through a third node to reach each other would have a distance of 2. Spring embedded visualization attempts to place nodes with similar geodesic distances to one another closer together on the visualized network map (Hanneman & Riddle, 2005). It's worth noting that in a pure two-mode network the shortest possible distance is 2, since the primary mode can only connect to the secondary mode (and vice versa). But again, in the hybrid networks of this study, some caution must be used when inspecting the graphs as primary nodes can directly connect to one another with a path length of one. Secondary nodes can still only do so with a path length of two, and these must past through a primary node. Superimposed on this nodal spatial arrangement, betweeness measures are visually identifiable based on node size. Primary nodes are indicated by circles while secondary nodes are shown as squares.

Final analysis was conducted by creating a series of network images bracketed by restricting the network to nodes of successively higher and higher betweeness scores. This series of images allows analysis of the network based on structural relationships as the core of the network evolves with the inclusion of more peripheral elements. The combined end results of this “hierarchical reduction” process is a map series indicative of influence levels in the network (Hanneman & Riddle, 2005).

Using these methods, structurally and analytically interesting network elements were identified for content analysis. A unique naming scheme was devised for each network and used as a framework for understanding the underlying trends and patterns of thought within each body of knowledge.

1.4 Content Analysis

I conducted content analysis on network-identified key-nodes. A two-step grounded coding method was used. Step one identifies the specific thematic focus area for each article independently. The second step used the coded results from step one to generalize larger themes across the sample set. These results were then interpreted in context of network position. Content analysis was conducted by reading core articles completely. The abstracts of articles from structural members were then read. Retrospectively, the order of this process core first, then structural members, all following the network analysis may have introduced bias into the abstract interpretations by imposing a need to understand the abstract content through the network framework and content of the core articles. In other words, the order of this process may have forced the desire to “see” the influence of the core articles in the structural papers, as well as similarities between co-members of the same structure. Assessments as to what degree and what interpretive impacts this may have had are discussed within each individual section below.

1.5 Individual Network Results and Discussion

1.5.1 Traditional Knowledge

In order to define the traditional knowledge network, I developed the following working question, “How has traditional knowledge been utilized in understanding environmental change in Alaska?” Key word searches were constructed around this question combining the term “Alaska” with 1) “traditional knowledge,” 2) “local knowledge,” 3) “indigenous knowledge,” and 4) “traditional ecological knowledge.” The differences between these terms warrant definition. Local knowledge is the foundation. It focuses attention on knowledge gained by an individual through lived experience in a limited geographical region. The salient feature to this definition is a focus on the individual and knowledge gained through that individual's experience with their environment (note: nothing is assumed about the nature of the environment, built or “natural”) Traditional knowledge, on the other hand, is generational in nature. Consequently, it represents knowledge gained through a group's individual environmental experiences tempered by knowledge accumulated through generations of experiences living in the same region (and/or conducted through similar lifeways as generations previous). Indigenous knowledge is summed up as traditional knowledge that is held by indigenous peoples of the world with distinctly different worldviews than Western societies that (can) result in equally distinct approaches to understanding and experiencing the environment. Traditional ecological knowledge is a Western concept that attempts to isolate the many-faceted cultural manifestations of a people's environmental knowledge and align it to purely Western concepts relevant to ecological questions and observations. This term, while common in current literature, is inaccurate in describing human-environment relationship and implies a certain degree of cultural elitism that can blind researchers to key observations. Differences between these terms are subtle but profound, and highly relevant depending on the temporal scale of environmental change being considered. Local knowledge would have a relevance to changes that occurred across a single lifespan's awareness, where as, traditional and indigenous knowledge have the potential to reach across lifetimes and detect slower rates of change (as does traditional ecological knowledge). Unfortunately, distinction between the terms are not widely appreciated and researchers often use them interchangeably, thus all were included in the Web of Knowledge word search.

Nineteen results were returned for the combined “Alaska” and “traditional knowledge” word search, eight for “Alaska” and “local knowledge”, thirteen for “Alaska” and “indigenous knowledge,” and twenty-seven for “Alaska” and “traditional ecological knowledge.” The network produced by these searches can be seen in figure 1.1.

Visualizations of this network produced an interesting dual limbed cluster pattern that originates close to the core of the network and (in this visualization) radiates to the left. A more diffuse, balanced region of the network develops on the right-hand side further from the core. The core of the network here is defined as those nodes with the highest betweeness scores (note: a factor outside the defined system of this network, as developed, is article publication date. This will have an impact on betweeness scores. Detailed treatment of this issue, however, is better suited to a temporal network study. This would be a beneficial parallel study to run, but beyond the consideration of this analysis.) At the highest levels, greater than 1700, a cluster of primary nodes connect to a single secondary node (Co1 in Figure 1.2). Two distinct and mutually disconnected primary nodes are evident and help to form a slightly disconnected core. Walking out from this core, betweeness >1000, this pattern of a developing, connected, central core with disconnected peripherals persists with each successive betweeness step.

As mentioned above, an interesting limbed structure radiates out of the main cluster of nodes in this network. This can be seen most predominantly in figure 1.2 by the nodes labeled A2-6 and B1-8 in figure 1.1. The more diffuse right-hand section of the network mentioned above is characterized by nodes labeled D1-4. Table 1.1 lists corresponding article titles and thematic content.

Articles in Cluster A are heavily concerned with topics related to climate change and driven by Western researchers seeking context to instrument based observations. Traditional knowledge (TK) seems to be approached in this portion of the network as a tool to be incorporated into the Western scientific process. Structure B, however, which is interestingly the section of the network with the strongest developmental pattern of a connected core with disconnected peripherals, is less thematically connected. Areas of focus in this structure vary from climate change to resource management, but an underlying theme seems to be that researchers are trying to understand TK as an additional and distinct way of knowing. Structure D is harder to thematically group, as might be expected given its diffuse network nature, but broadly, might be characterized as research that explores how TK is transferred within and between cultural groups. As can be seen in figure 1.2, nine isolate nodes exist in this network that are completely disconnected from the main network component. These nodes do, however, seem to be thematically linked by a focus on site specific issues and challenges, and tend be the products of workshops or planning events rather than discrete academic-based research efforts.

The results from the combined network and content analysis would indicate four main ways that work involving TK is being applied in Alaska. Each is predominantly concerned with understanding and responding to rapid environmental changes. The first, represented by structure A, is focused on identifying indicators of climate change. These articles, generally, utilize TK as a supportive tool in corroborating instrumental observations and theoretical results of climate warming in the state. The second, represented in structure B, is less cohesive in specific study questions (visible in the network through the less connected nature of this limb) but more unified in the approach to considering TK as a unique way of knowing that adds depth to Western understanding rather than simply another data source to be incorporated into ongoing studies. More interest seems to be focused on how TK can inform pertinent study questions early in the research process. Structure D seems supportive of these other two structures through a focus on understanding the transfer of TK related thought. The fourth, represented by the isolates, is concerned with regional and local solutions to human-environmental issues. The disconnected nature of these works is likely a function of citation practices between the formats of the report styles rather than a disconnect between bodies of knowledge drawn upon as information sources. These results would indicate that my own work likely straddles structures A and B in identifying the broad sweep of possible climate change impacts, as well as, providing data defining to what extent these impacts are affecting day-to-day life choices. Further, it heavily draws upon Structure D in understanding information transfer through the new medium of social media. Of course, the purpose of my work is ultimately to enhance place-based decision-making.

The very fact that each structure identified is tied to a theme of my own work is suspicious and suggests some level of unconscious bias in the network development and analysis outlined above. However, the results are still useful in placing my work in context to others' efforts through the structural differentiation of themes. Additionally, a large portion of the bias mentioned above may simply be attributable to the Web of Knowledge database sourced in this study. Absent in the results is a strong Native voice, because of this, it is likely this network is most representative of Western efforts at understanding the role TK can play in the development of a predominantly Western understanding of human-environmental interactions. Thus, it should perhaps be no great surprise that as a Western researcher I would be at least somewhat aligned to these goals.

1.5.2 Social-ecological Systems in Alaska

To explore research in social-ecological systems (SES) in Alaska I phrased the following driving question, "What are the key environmental and research methodologies used to frame the concept of SES in Alaska?" This resulted in the following search terms being developed in conjunction with the spatial locator "Alaska:" 1) "integrated assessment" (returned 8 articles), 2) "climate modeling" (returned 3 relevant articles), 3) "landscape change" (returned 6 articles), and 4) "social ecological systems" (returned 23 articles).

Network analysis for the SES network resulted in the hierarchal regression seen in figure 1.3 using the same betweeness procedures as the TK network. At the core, this network can be described by a large number of high betweeness primary nodes surrounding one core secondary node. Not all central primaries are connected to the core element. This pattern persists until betweeness scores greater than 500 are included in the graph, at which point a swarm of secondary nodes enter the network. This would indicate an overall diffuse network core that is well interconnected through peripheral, primarily secondary, nodes. This may represent an evolving state of knowledge that is defined by a diverse range of research topics addressed via a large common pool of literature. Notable here, while not quantified in this work, is an impression that papers published through this line of study seem to have much higher numbers of references cited as sources. This is likely a citation norm created by the integrated and interdisciplinary nature of the field, which requires a greater breadth of knowledge than more disciplinary work, questionably, at the expense of content depth. A network consequence of this practice may very well be the explosion of low betweeness secondary nodes in the last step of the hierarchal regression.

No strong structural features can be seen in this network. Rather, it is fairly balanced and symmetrical in shape, with a tightly bound core and more loosely connected periphery. This is a result that you might expect in a dynamic learning community that is essentially unified in its purpose but diverse and open in the methods used to achieve it. This is seemingly very different than the TK network, which feels much more, disjointed in its purpose as a whole.

Based on the combined analytical and visualization techniques, figure 1.4 illustrates specific nodes chosen for qualitative review. Table 1.2 correlates these nodes to article titles and thematic coding. As mentioned, this is a structurally balanced and connected network; this tendency was carried over into the content analysis results. Essentially all core network members were thematically concerned with climate change as a driver of SES change. Variations in these core articles tended to be defined by the specific type of climate driven impact being explored in individual pieces of research.

All were concerned with multiple cross-scale linkages within the system and specifically the resilience, vulnerability, and sustainability of community and regionally based social systems. Content differences were slight between articles in the A and B network structures. Both drew heavily upon the common synthesis of potential climate change ramifications outlined in the Co1 article, predominantly relating to phase change issues surrounding increased temperature across the freezing point of water. Articles identified as part of the A structure typically were concerned with simply defining and understand specific, locally placed, social-ecological system in a regional context. Structure B articles were focused on understanding the same type of system interactions, but were equally concerned with proposing and testing tools to manage natural resources from an SES perspective under these changing conditions. However, there were clear overlaps in theme content between structures, reinforcing the idea that SES research in Alaska is centered around an active, aligned, core group of researchers that draw resources from a wide variety of both disciplinary and interdisciplinary resources. Apparent in most articles reviewed was an appreciation for the ability of locally lived experiences to inform instrumental observations of environmental change. It is through this aspect of SES study that my own work can most clearly contribute to the academic advancement of the field.

1.5.3 Facebook

Development of the network defining relevant Facebook research was based on trying to understand the ways by which Facebook activity acts as documentation of user's lived experiences. The search terms “identity,” “real-world,” and “social movements” were each uniquely combined with the term “Facebook” to generate the primary mode data. The subsequent network created by linking cited sources to primary nodes could be seen in figure 1.5. A similar limbed pattern as found in the TK network is apparent, as is a set of isolate articles unlinked to the main network component (figure 1.5, nodes labeled O1-6). This again would seem to structurally indicate the pursuit of a broad, un-consolidated research agenda around Facebook use. This is likely not surprising considering the relative newness of this form of communication and the huge spectrum of lived experience that is conveyed, and publicly accessible, through it.

Content analysis of defined network structures (table 1.3) identifies some thematic alignment across the network. The most central article, Co1, is a review work, which attempts to define a framework that recent Facebook research can be organized through. Critically, it defines five categories that Facebook research can be sorted into 1) social interactions, 2) identity formation, 3) privacy issues, 4) user descriptions, and 5) motivations for use. To a certain extent, content differences between network structures align with this framework. However, procedurally it must be noted that the methods of this study dictated that the core article be read in detail prior to content analysis on other network members. This undoubtedly colored their eventual interpretation. Conversely, alignment with the above categories would be expected if this core article were accurate in its assessment of the current state of research. In that case, a matching of network structure with the identified categories would support the validity of the network approach taken in this study and also support the original identification of these categories.

Generalizing, articles in Structure A deal with issues of privacy. Structure B's focus is more on investigating users reasons for interacting through Facebook. Structures C and D deal with the social impacts and interactions of individuals communicating through Facebook (as well as generalized across other social media platforms). In these structures (C and D), a particular influence is placed on the interplay between a user's online and offline worlds. Isolates O1-6 also tend to follow this thematic trend, but, perhaps originate from different parent disciplines (as evidenced by publication source), the exception being O5 which explores social network theory through data obtainable via web-based sources and practices and is therefore a thematic outlier as well as a network isolate.

Taken together, the thematic content and network structure of this body of knowledge would seem to indicate a field of study that is quickly coalescing around some dominant concepts but is still early in its development. It seems likely as the network evolves themes centered around social interaction, specifically focused on the interplay of users online and offline worlds, will come to dominate the field. Motivations for use should necessarily be wrapped up into these main concepts as the field matures. Privacy and user descriptions seem destine to slip away to niche studies as the use of social media becomes more ingrained in everyday cultural institutions at deeper and deeper levels. Many of the works reviewed in this network relied on the social media behavior of undergraduate college students as sample sets. This research strategy is fraught with methodological challenges and limits the usefulness of these studies in applying them to broader settings. Future work seems likely to address this issue, my own work as an example, as researchers begin to pursue social questions answerable through Facebook rather than simply about Facebook.

1.6 Conclusion

The combined bodies of knowledge represented in these networks form the academic foundation that my master's thesis rests upon. Individually, the construction of these networks provides a systematic way to connect and visualize the patterns of thought within each knowledge pool. They provide a literal map to use as a guide in tracking down the origins of ideas within each. Like any map, however, they are just representations of the “knowledgescape” that my work explores. As I start to delve into my own data and interpret its meaning in relation to other work, these maps present a multi-scaled perspective that a more typical literature review may not provide. The difference is the broader context that networks provide, which in this case, informs not just on specific content or ideas within a particular piece of work, but also the larger scaled perspective through which those ideas connect to other work from the intent of their authors (through their citation practices), and not based purely on how my own research biases would have them.

All three lines of inquiry that these networks illustrate are relatively new fields of academic study. They are each interrelated in their response to modern societal pressures in their interdisciplinary approach to grappling with emergent global environmental and technological challenges unheard of to previous generations of researchers. The SES and TK research fields in Alaska, however, are very tightly connected, sharing both specific articles, as well as, some guiding research themes. Predominantly, they each share an acknowledgment that the accumulated experiences of an individual's life on a given landscape are valuable. Further, that they are capable of detecting subtle (and not so subtle) environmental changes within their sphere of observation. A difference is that in the study of TK the process of accumulating knowledge (and thus communicating, “For how can one accumulate knowledge without the communication of that knowledge by someone, or something in the first place?”) is a primary thread of study. SES approaches TK from a more pragmatic perspective and looks at this form of knowledge as just one of many resources to be applied to solving modern social-environmental challenges. Placing my own research into this context, it is clear that my work aligns with the SES mindset. However, it is equally clear that to utilize TK in such a pragmatic way undervalues the reflexivity of the knowledge accumulation process and attempts to isolate desired forms of data from the holistic cultural influences that give it value in the first place. Researcher-initiated and guided communication with knowledge-holders can only begin at the base level of the researcher and therefore is necessarily framed by the researcher's understanding (and assumptions) of the system under question.

Facebook research offers the investigator a window into the reflexivity of the TK process among participants without researcher influence. The state of research in this field is extremely young however, and the foundational communication theory needed to do this is just starting to be applied. The majority of work to date has been focused on descriptive behavior that is context dependent and seriously draws into question methodologies that extrapolate across sample set demographics to larger or culturally distinct populations.

The network analysis approach to this literature review allows for specific portions of each network to be identified and focused on to support my own work. Specifically, in the TK network the D structures that focus on the knowledge transfer process are important. Though, likely easy to have overlooked in a non-networked review where articles more directly related to TK and issues of climate or landscape change would have been most likely to seem relevant. Facebook research that focuses on communication theory rather than descriptive use, ties well with this side of the TK network. Each of these then fit in support of methodological improvements across the breadth of themes in the SES network. That network is clearly where my work is the most natural fit and has the most to offer in advancing academic understanding.

1.7 Figures

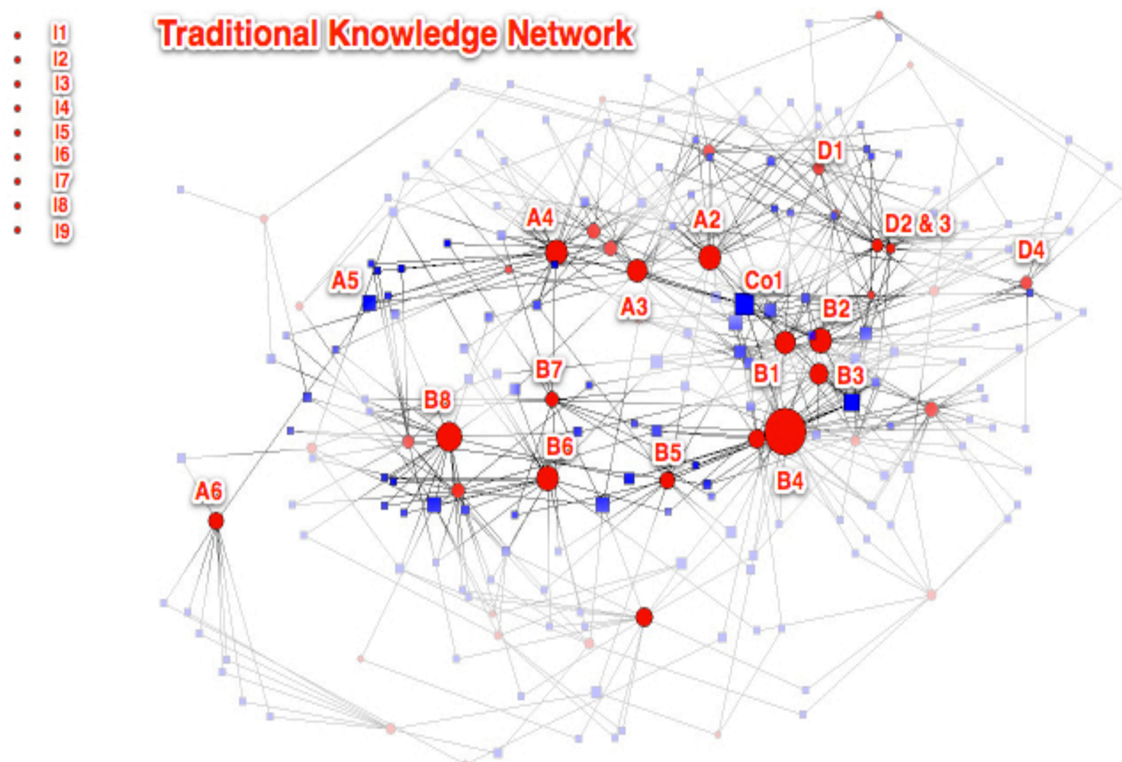

Figure 1.1 Traditional Knowledge Network. Red circles represent original returned Web of Knowledge search results. Blue squares represent the shared sources these articles cited. The size of nodes is indicative of betweeness centrality scores, larger being more central. Alphanumeric labels correlate to structural positions detailed in table 1.1.

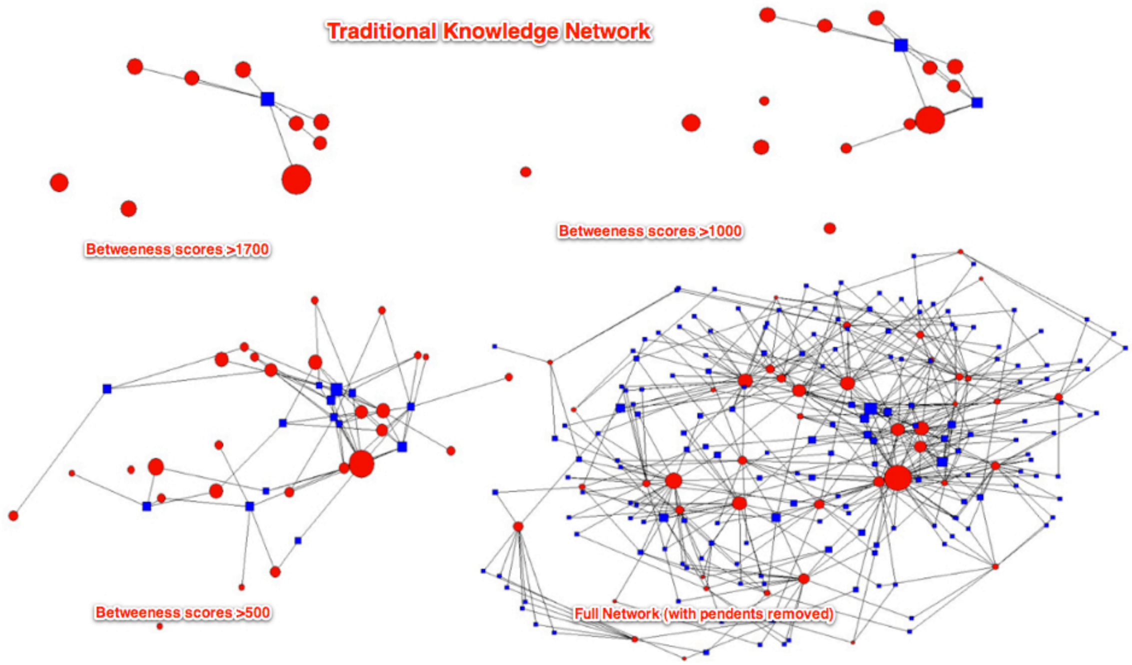

Figure 1.2 Traditional Knowledge Core-peripheral Relationship Maps. Red circles represent original returned Web of Knowledge search results. Blue squares represent the shared sources these articles cited. The size of nodes is indicative of betweeness centrality scores, larger being more central. The presentation of network evolution based on betweeness scores allows for core-periphery relationships to clearly be illustrated.

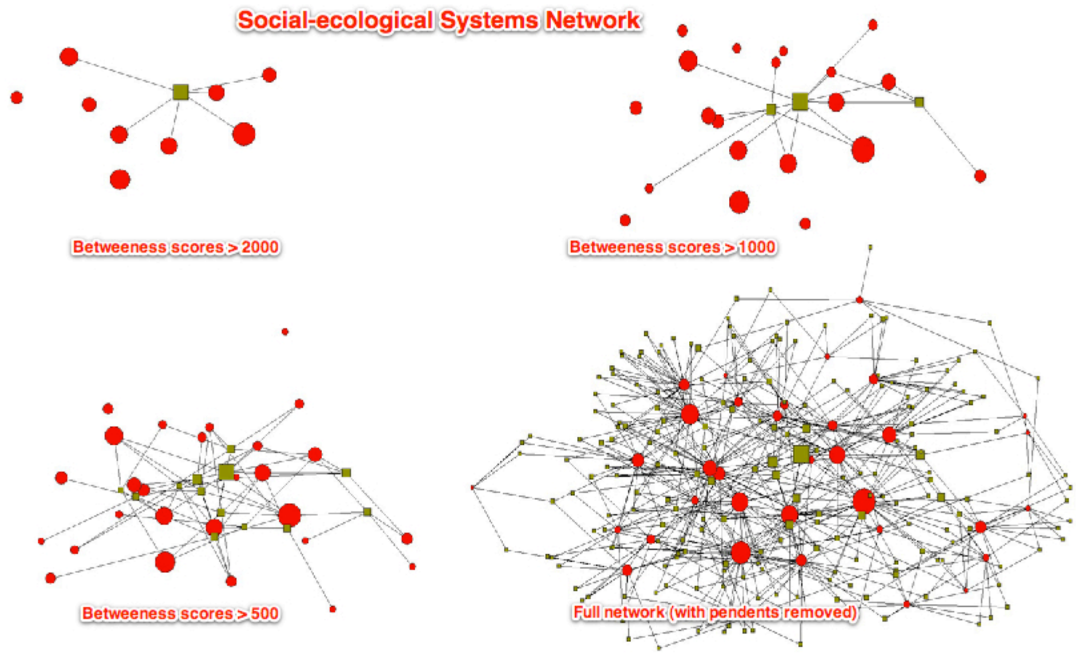

Figure 1.3 Social-ecological Systems Core-peripheral Relationship Maps. Red circles represent original returned Web of Knowledge search results. Green squares represent the shared sources these articles cited. The size of nodes is indicative of betweeness centrality scores, larger being more central. The presentation of network evolution based on betweeness scores allows for core-periphery relationships to clearly be illustrated.

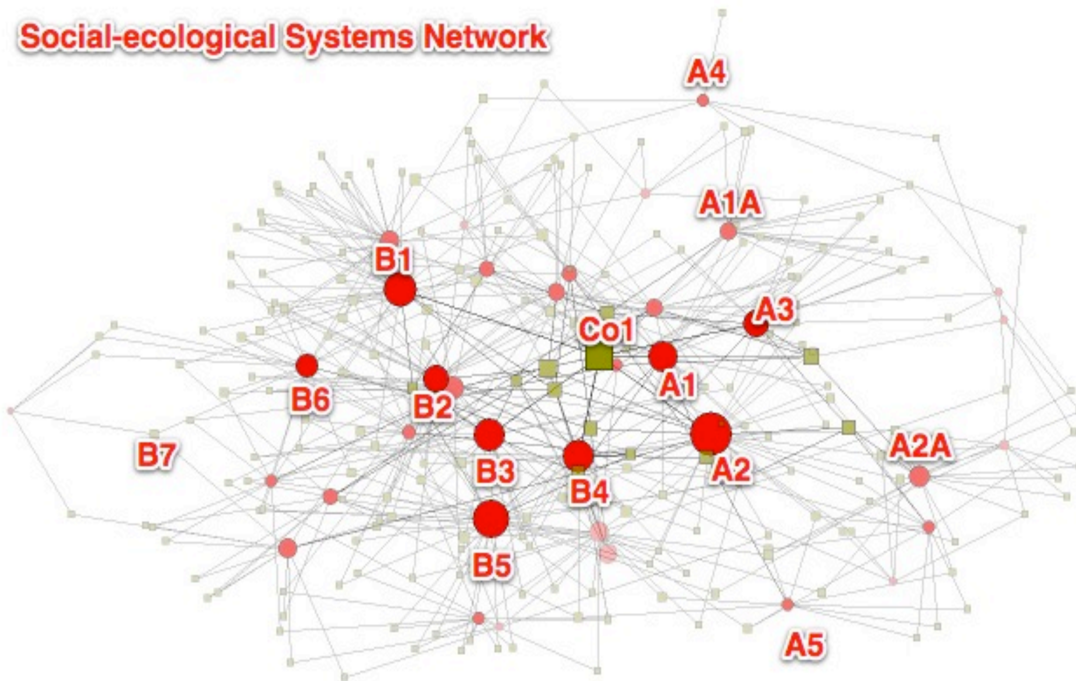

Figure 1.4 Social-ecological Systems Literature Network. Red circles represent original returned Web of Knowledge search results. Green squares represent the shared sources these articles cited. The size of nodes is indicative of betweeness centrality scores, larger being more central. Alphanumeric labels correlate to structural positions detailed in table 1.1.

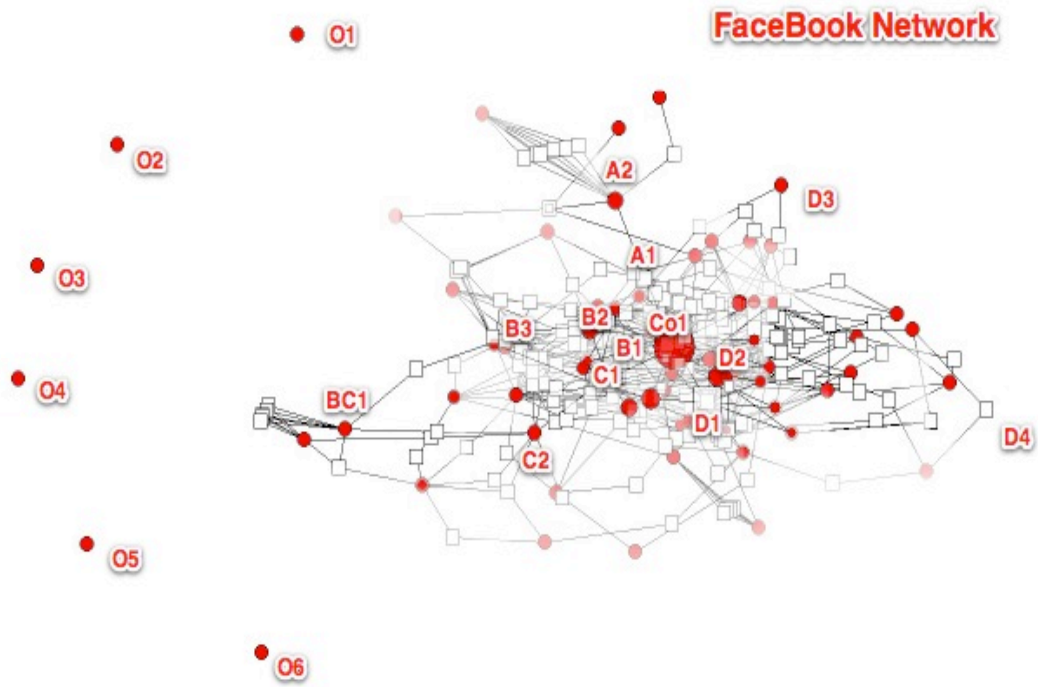

Figure 1.5 Facebook Literature Network. Red circles represent original returned Web of Knowledge search results. White squares represent the shared sources these articles cited. The size of nodes is indicative of betweeness centrality scores, larger being more central. Alphanumeric labels correlate to structural positions detailed in table 1.1.

1.7 Tables

Table 1.1. Traditional Knowledge Literature Set. Table of articles and theme correlated to network structural position.

Location	Node	Title	Theme
Core	Co1	Title: Glaciers and climate change: Perspectives from oral tradition	Climate change, local knowledge to inform science, historical perspective, TK as knowledge not data
Struct. A	A2	Title: Total Environment of Change: Impacts of Climate Change and Social Transitions on Subsistence Fisheries in Northwest Alaska	Climate change, ethnographic, interviews/participant observation
	A3	Title: Advancing Landscape Change Research through the Incorporation of Inupiaq Knowledge	Climate change (lake drainage), interviews,
	A4	Title: Perception of change in freshwater in remote resource-dependent Arctic communities	Climate change (prec. and temp.), interviews
	A5	Title: Observational evidence of recent change in the northern high-latitude environment	Climate change, research synthesis of TK, science tied to TK, modeling support
	A6	Title: Modeling sustainability of arctic communities: An interdisciplinary collaboration of researchers and local knowledge holders	Climate change, integrated research, sustainability
Struct. B	B1	Title: Communicating traditional environmental knowledge: addressing the diversity of knowledge, audiences and media types	TK as distinct way of knowing, communication modes
	B2	Title: Integrating Traditional and Scientific Knowledge through Collaborative Natural Science Field Research: Identifying Elements for Success	TK supportive of instrumental observations
	B3	Title: Traditional knowledge of the bowhead whale (Balaena mysticetus) around St. Lawrence Island, Alaska	TK to identify areas of focus for scientific research
	B4	Title: Observations on the utility of the semi-directive interview for documenting traditional ecological knowledge	TK as distinct knowledge pool, Methods to access, communication modes
	B5	Title: A Case for Developing Place-Based Fire Management Strategies from Traditional Ecological Knowledge	TK as a replacement of Scientific gaps of understanding, sustainability, place-based
	B6	Title: Sustaining a healthy human-walrus relationship in a dynamic environment: Challenges for co-management	Climate change, social-ecological systems, sustainability, place-place based, resource management
	B7	Title: The significance of context in community-based	Climate change, TK as

Table 1.1 Continued

Location	Node	Title	Theme
		research: Understanding discussions about wildfire in Huslia, Alaska	distinct knowledge pool, resilience/sustainability, communication modes, natural resource management
	B8	Title: Arctic climate change discourse: the contrasting politics of research agendas in the West and Russia	Climate change, resource management, TK as distinct way of knowing
Struct. D	D1	Title: Arctic marine mammals and climate change: Impacts and resilience	Biology, marine mammals, sea ice climate change
	D2	Title: Producing an Indigenous Knowledge Web GIS for Arctic Alaska Communities: Challenges, Successes, and Lessons Learned	Technology, communication,
	D3	Title: Transmission of Environmental Knowledge and Land Skills among Inuit Men in Ulukhaktok, Northwest Territories, Canada	TK knowledge transfer
	D4	Title: Natural history and conservation of the Greenland whale, or bowhead, in the northwest Atlantic	TK to fill scientific gaps
Isolates	I1	Title: Total Environment of Change: Impacts of Climate Change and Social Transitions on Subsistence Fisheries in Northwest Alaska	Repeat- network error in names. See A2
	I2	Title: Proceedings of the North Coast Eulachon Workshop:	Species focused integrated research, TK as distinct way of knowing, place-based
	I3	Title: Alaska communities and forest environments: A problem analysis and research agenda.	Resource management, TK as research consideration, place-based
	I4	Title: The indigenous worldview of Yupiaq culture: Its scientific nature and relevance to the practice and teaching of science	Cultural context to science education, place-based
	I5	Title: Rural participatory research in Alaska: The case of Tanakon village	Local knowledge, place-based, localized research adaptation
	I6	Title: Participatory Action Research - Through Practice To Science In Social-Research	No abstract
	I7	Title: Development of a community-based monitoring and surveillance database on ecosystem health for interior Alaska.	No abstract
	I8	Title: Partnerships and cooperative resource assessment in Alaska: Developing a shared vision for subsistence fisheries management	No abstract

Table 1.2. Social-ecological Systems Literature Set. Table of articles title and theme correlated to network structural position.

Location	Node	Title	Theme
Core	Co1	Climatic Change	Scientific, instrumental observation, overview of climate change impacts, call for increased monitoring, values TK, Arctic wide
Struct. A	A1	Canadian Journal Of Forest Research	Boreal forest (moose), Subsistence impacts driven by climate change, co-management solution, institutional (formal and informal) interactions, Resilience, Interdisciplinary
	A2	Regional Environmental Change	Context based understanding of climatic changes, Local knowledge advocates, review study of other work, Interdisciplinary
	A3	Environmental Management	Vulnerability, local context, water resource, planning tool
	A1A	Global Environmental Change-Human And Policy Dimensions	Vulnerability, multi-scale (local and regional), natural and social indicators
	A2A	Cold Regions Science And Technology	Integrated assessment, climate change, vulnerabilities, coastal impacts, natural and social indicators, planning tool
	A4	Journal Of Applied Ecology	Multi scaled, natural science focus, climate a change driver
	A5	Ecosystems	Climate a change driver, interdisciplinary study, local context, TK integration, sustainability, caribou, subsistence impacts,
Struct. B	B1	Global environmental change-human and policy dimensions	Climate a change driver, subsistence impacts, combines TK with metrological data
	B2	Arctic	Cross scale interactions, regional policy, natural resource management, climate a change driver, case study, social science focus
	B3	Proceedings of the national academy of sciences of the united states of America	Cross scale interactions, regional policy, natural resource management, climate a change driver, case study, sustainability
	B4	American naturalist	Cross scale interactions, regional policy, natural resource management, climate a change driver, natural science focus, sustainability
	B5	Ecological applications	Social science focus, Cross scale interactions, regional policy, natural resource management, climate a change driver,
	B6	Ecology and society	Regional policy, natural resource management, TK dependent
	B7	Oecologia	Natural science focus

Table 1.3. Facebook Literature Set. Table of article title and theme correlated to network structural position.

Location	**Node**	**Title**	**Theme**
Core	Co1	Title: A Review of Facebook Research in the Social Sciences	Define broad research objectives, research review, describe users, identity presentation, FB in social interactions, privacy
Struct. A	A1	Title: Facebook and Online Privacy: Attitudes, Behaviors, and Unintended Consequences	Privacy, enmeshed in lived-experience, FB specific
	A2	Title: Social Media and the Activist Toolkit: User Agreements, Corporate Interests, and the Information Infrastructure of Modern Social Movements	Privacy, social interactions, corporate policy, Arab spring, multiple platforms
Struct. B	B1	Title: Predictors and consequences of differentiated practices on social network sites	Reason for use, multiple platforms, gender differences (women = stronger tie activity), user descriptions
	B2	Title: A generational comparison of social networking site use: the influence of age and social identity	Reason for use, User descriptions, self-esteem = peer communication & identity gratification, < self-esteem = social compensation
	B3	Title: "There Isn't Wifi in Heaven!" Negotiating Visibility on Facebook Memorial Pages	Privacy-context collapse, reasons for use, mourning, FB specific
Struct. AB	BC1	Title: A movement of connected individuals: Social media in the Austrian student protests 2009	Social interactions, online/offline interaction, in-group/out-group dynamics and community building, multiple platforms
Struct. C	C1	Title: Social network sites: Definition, history, and scholarship	Multiple platforms, overview and definition of terms
	C2	Title: Social media and social movements: Facebook and an online Guatemalan justice movement that moved offline	Social interaction, Facebook specific, online/offline connections
Struct. D	D1	Title: The benefits of Facebook friends: Social capital and college students' use of online social network sites	Social interaction, Facebook specific, online/offline connection, social capital
	D2	Title: Me and My 400 Friends: The Anatomy of College Students' Facebook Networks, Their Communication Patterns, and Well-Being	Social interaction, Facebook specific, online/offline connection

Table 1.3 Continued

Location	Node	Title	Theme
	D3	Title: Communities of participation: A comparison of disability and aging identified groups on Facebook and LinkedIn	Social interaction, spatial displacement of distributed communities, multiple platforms
	D4	Title: Birds of a feather: Homophily in social networks	Social interaction, tie formation processes
Outlier	O1	Title: Facebook: Corporate Hackers, a Billion Users, and the Geo-politics of the "Social Graph"	Ethnography of FB corporate headquarters
	O2	Title: Football Sub-Culture and Youth Politics in Algeria	Social interaction, identity formation, online/offline interactions
	O3	Title: From the street to Web2.0 Bolivian highland dancing as a generator of identity and ethnicity- A cyber anthropological study	No abstract
	O5	Title: Local Community Detection Using Link Similarity	Network analysis
	O6	Title: Trust as the basis of coalition formation in electronic market places	Trust, commerce, social interaction, multiple platform

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Chapter 2:

Identifying SES in Community-based Social Media Networks

2.1 Abstract

Growing awareness that the earth has shifted into the anthropocene, characterized by persistent environmental change linked to human action, requires new tools of analysis in order for societies to remain within sustainable planetary operating boundaries. This work explores the possibility of taking advantage of widespread online social media participation to develop a tool for doing so. While global in scope, the impacts and consequences of the anthropocene are felt most intimately at the individual level and are socially expressed through interpersonal communication at the community level. Therefore, this exploratory work focuses on a need to identify and assess local level social-ecological system (SES) relationships. To do so, spatially grounded public exchanges on the social media website Facebook are examined with two primary goals in mind: 1) examine the types of SES content being passed through this communication medium, and 2) develop a practical system for monitoring and interpreting these communications signals. Two communities from the same broadly defined region in rural Alaska were selected as case studies. Communication patterns were assessed using a combined content and network analysis methodology. Results clearly indicate that SES signals are passed through this mode of communication, and that a systematic method can be developed applicable to a wide range of community development and resource management questions including infrastructural development, non-renewable resource extraction, and fish and game regulations.

2.2 Introduction

Facebook and environmental change, primarily via shifts in climate norms, represent two of the most significant social and environmental phenomena affecting the world today. Facebook, if it were a country, would be the third largest nation on the planet, with more than 800 million active users (Facebook, 2011). Only India and China would be larger (Central Intelligence Agency, 2012). Climate induced environmental change, on the other hand, threatens the entire globe through a variety of processes from increased storm frequency and intensity to widespread biome shifts and altered fire regimes (Emanuel, 2005). These changes interact with human societies on many levels. Coastal flooding from increased storm intensity and frequency, compounded by rising sea level is one example (McGranahan, Balk, & Anderson, 2007). Food security issues brought about through a combination of shifting precipitation patterns, maladjusted agricultural practices, and landscape degradation is yet another (Howden et al., 2007). Facebook offers unprecedented access into the everyday life experiences of its users. This access represents a powerful new opportunity to gain insight into the social-ecological adaptation patterns around these issues. It requires usable research protocols are developed in order to take advantage of this opportunity.

The Polar Regions, meanwhile, are experiencing increased warming relative to the lower latitudes, and as a consequence, increased rates of environmental change (Hinzman et al., 2005). Study of how the societies of the north adjust to these changes represents an early opportunity to gain valuable baseline insights into foundational SES processes. This could have potentially widespread value as greater numbers of diverse social-environmental systems adjust to the demands of the anthropocene in the near future.

Because of the increased rates of environmental change in the region, Facebook communication patterns are likely to express signals of user experienced social-ecological change and real-time adaptation strategies. This makes the region a likely place to develop research protocols that use Facebook communication patterns as a data source.

The subsistence life-way that is practiced in many northern communities requires that residents are highly attuned to environmental conditions. Additionally, the long cultural history of practicing this life-way enhances environmental awareness through the generational transmission of traditional knowledge. This deep cultural knowledge of local environmental conditions allows for meaningful insights into not only current climate related issues, but also how current conditions differ from past conditions. However, worldview differences combined with logistical challenges (often, financial and time related) can create difficulties in building research partnerships between outside investigators and high latitude rural communities. The increasing infrastructural development of digital communication technology (Terra, 2010), and subsequent local use of social media, potentially affords the opportunity to alleviate some of these logistical challenges and improve our understanding of social-ecological systems through enhanced community-researcher relationships. This opportunity, combined with the relevance of social-ecological relationships to local residents, further situates the region as a prime location to explore a methodology that uses social media as a social-ecological system-defining tool.

Doing so represents a novel new way of approaching social-environmental studies in the north. Many questions are yet unanswered regarding social media use in high latitude communities, such as, “What is the degree of social-ecological information contained within this mode of communication?” And, “Is the development of a robust and practical study methodology feasible?” In this research I take an initial step at addressing these issues by focusing on the question of what types of social-ecological information are exchanged via spatially grounded Facebook use and how can this information be understood. To do this, I combine a deductive and inductive coding system to analyze content exchanged through Facebook. Once coded, network analysis is applied to identify discrete SESs expressed through this mode of communication. I propose that this methodology is a viable monitoring and assessment system for incorporating Facebook derived information into broader SES understandings.

2.2 Methods

The methodology I developed in this study focuses primarily on systematic and reproducible data collection and data analysis techniques. Data collection is centered around three principal phases: sample selection, data draw, and data processing. Analysis is premised on exploring the data from a community perspective. Community-based relationships are comparatively examined between two regional neighbors. Network analysis is used to explore relationships within and between the communities. Network measures are examined at both the nodal and network-wide scales. The combination of these scales of analysis allow a nuanced view of how individual experiences are translated into broader societal understanding through Facebook communication.

2.3.1 Sample Selection

Northwest Alaska was chosen as the regionally defined field area for this study. The approximate geographic boundaries of which can be seen in figure 1 above, and which is defined by broadly shared geophysical and cultural characteristics relevant to subsistence life-ways. Two rural communities within this region were selected as distinct units of measure. Because this is a study of SES understanding communicated through virtual-space, it must be understood that defining an absolute geographic boundary is problematic. The idea of a spatially defined field area in this case is best considered as a system-grounding tool. Given this, the individual Facebook users in the two communities, A and B, identified in figure 5 define the initial sample population. The end population is bounded by the Facebook communication networks of these users.

The goal of all social media sites is to help users connect with other users. Therefore, each site provides internal platform tools to do so. As Facebook is aimed at promoting virtual communities that are founded on real-world relationships, one of the tools they have developed is a search feature to find users from specific locations. This study utilizes the "find friends from..." tool to identify a census of all users who self-identify with living in the communities of interest and have configured their privacy settings to allow public viewing of their Facebook "wall" content. The activity of these users on their individual walls then comprises the core data set I use in the study. Table 2.1 illustrates the sample size of each community in the study in relation to overall community population.

2.3.2 Data Draw

Once the census population of Facebook users is defined, the task of filtering the wide variety of information that is communicated through Facebook by this population is begun. This process presents two important obstacles: 1) is to determine exactly what aspects of Facebook communication to track (e.g., text-based wall posts, posted links, posted videos, posted pictures, “likes,” ”comments,” etc.), and 2) is to define which of the many content themes communicated through this medium are relevant to the study question.

Facebook offers a variety of communication tools through which its users can interact with one another. Only text-based wall posts were examined in this work. On many occasions the posting of photos, videos, and links to other web-based resources are associated with a user's wall activity. When this occurs analysis of these posts is based solely on the user's own textual comments regarding that media. Particularly, the posting of user-generated photos is a common practice on Facebook and important social-ecological relationships can be drawn from researcher-based interpretation of the imagery. However, that level of researcher reflexivity was not desirable here. Therefore, photos, or any other form of media, that users posted to their walls are not included in the data draw if they were not accompanied by a user generated text-based comment. Summarizing then, the data draw process only pulled information from the user-generated, text-based, wall content of the sample population. This excludes any content posted by others on a individual user's wall or any media posted by the user unaccompanied by text-based commentary.

As can be imagined, a large volume of the information conveyed through wall activity is not related to SES issues. Some technique then is required to filter through this content and pull out study relevant content. A deductive process, based on the researcher's established knowledge of the system issue being investigated is used to create this filter. This step in the overall method formally defines what will, or will not, be considered an SES signal for any specific study context. For my work, the study population was chosen based on the assumed attuned environmental awareness required to practice a subsistence life-way, therefore, an SES-based deductive framework was tailored to this life-way. Initial filtering of Facebook wall content is based on this framework and identified via the code-phases, weather, hunt, gather, food, environment. These code-phrases are defined in table 2.2 and were chosen to capture aspects of the subsistence life-way from experiences out on the land (hunt, weather, gather) to those in the home (food). The phrase “environment” was included as a miscellaneous term in recognition of the limited nature of the other four to capture the full range of subsistence related experiences conveyed through Facebook, and to include a qualitative mechanism for study-relevant posts to be captured even if they don't precisely fit the deductive filter guidelines. An example might be a post discussing fixing an outboard motor “to go to camp.” This is clearly a relevant part of the subsistence system, and thus meets the intent of the deductive filter, while not precisely fitting into any of the defined categories.

I have defined a clear boundary on what Facebook actions are to be assessed in this study. I also laid out the deductive framework that is used to filter through the variety and volume of content posted to Facebook and acts to define what content-based actions will be identified as signals of SES communication and what will not. I can now describe the full procedure for data collection during the data draw phase of research.

The draw period occurred from August 8, 2012 until through January 10, 2013. This is an important period in relation to late summer gathering, fall hunting, and winter travel. It also captures fall freeze-up. The data draw consists of manually reviewing all wall content for each community user that is posted during the sampling period. Posted content is scanned and filtered based on the deductive code framework described above. Posts that were found to fit the deductive coding scheme were archived for closer study during the data processing stage of research. A total of 637 unique posts were saved.

2.3.3 Data Processing

Once I filtered for relevant data, I processed the saved posts for two key aspects. These were 1) the development of an inductive coding system, and 2) identification of the Facebook user network interacting with each unique post. Processing the data for these two types of information, I was able to define inductively grounded SES components from Facebook content while simultaneously mapping the social influence of each.

The relationships between the deductive and inductive codes act as a bridge between individual-community level social-ecological perceptions and broader SES concepts in sustainability science. The inductive code is developed by capturing key-word style terms directly from the raw user-generated posts and organizing them based on the rubric in table 2.3. Clearly, more than one code can, and usually is, associated with each unique post.

The user network associated with these codes was developed by capturing the

Facebook names of all users who either “commented” or “liked” the individual posts associated with each code. However, two viable options exist in determining the potential social connections surrounding any unique content a user posts to their wall. First, the total “friend” network of the user could be identified, as this pool of people represents the first-degree network that could potentially view any given post by a specific Facebook user. However, it is more meaningful to define the social networks surrounding posting activity by those users who took some sort of conscious action to become involved in the content. In the instance of “commenting,” rich communication can occur where meaning and understanding are publicly negotiated between participants in full view. “Liking,” however, carries explicitly less public information. The intent of a “liking” action is highly context-dependent and variable based on the relationship between participants. While these two actions carry different levels of meaning between both participants and observers each indicates an active participation in the conversation and is treated equally for the scope of this study.

2.3.4 Network Analysis

I conducted analysis for each community as follows. Two distinct two-mode networks were created for each community. The first examines the relationship between individual Facebook posts to the combined deductive/inductive coding scheme. Node level measures are calculated (specific to two-mode networks) to determine the centrality of each node. Measures from these networks are used to address the question of which code terms are most actively discussed within Facebook-based communication channels. Degree centrality is used exclusively at this stage of analysis and is applied to illustrate the relative importance of one code to another. A second set of networks is analyzed in the same manner defining posts-to-people relationships.

The two types of community-based networks above share the common mode of individual Facebook posts. This allows a third network visualization to be constructed that illustrates SES components, as indicated by the code phrases, in relation to the potential social reach of the Facebook posts where they are discussed, as defined by the post-to-people networks. These visualizations are created by using the post-to-code network as a foundation, applying centrality measures from this network to the code phrases and then applying the post centrality measures derived from the post-to-people networks to the post nodes. Again, this can be done because the post nodes in both networks are identical. The result is a visualization that graphically illustrates the relative importance of individual SES components, as indicated by code phrases, to the potential social reach these topics have indicated by how many people were actively involved in those posts.

However, important structural relationships cannot be determined from just a simple nodal level analysis. There are visually obvious structures within the network graphs that need to be examined. Specifically relevant to identifying the SES information conveyed via Facebook, are network density relationships between code phrases.

Examining this, I looked at code-phrase affiliation relationships for each post-to-code network. The resulting networks examine the relationships between code phrases directly. Affiliation networks are built by creating a tie between nodes within one mode of a network when they share a tie with the same node of the second mode. Put another way, in the affiliation networks below a tie has been created between each code phrase that co-occurred in the same Facebook post(s).

Once the post-to-code affiliation networks are built a combination of network faction and clique analysis techniques are used to define subgroups within the larger network. Both analysis techniques use density relationships as their guide. Density in networks is a measure that compares the ratio of ties a node has with other nodes in the network to the total number that node could have if it were connected to every other node. Factions in network analysis force network data into a defined number of partitions, placing every node in a group and attempting to maximize density within each group. Cliques identify node sets that are already at maximal density. Clique analysis does not require all nodes to be in a group. Together they provide separate, but complimentary, views of potential network subsystems (Borgatti, Everett & Johnson, 2013).

Faction analysis shows partition divisions are created to maximize the density of node connections within each partition, yet still place every node in a partition. The success of these groupings is assessed via a fitness score that compares the actual faction densities (as a group) to their theoretical maximums (Borgatti, Everett & Johnson, 2013). The important consideration when looking at faction results is that the researcher defines the number of partitions to subdivide the network into and every node must belong to one of these groups. This draws in weakly connected outliers that might be better understood outside of any formal groupings. Because of this inclination to the general, and because the researcher must predefine the number of groups the network is partitioned by, faction analysis offers only a limited perspective on network subgroup structure. Therefore faction analysis is run in unison with clique analysis to add increased perspective on potential subgroups within the larger network systems.

Cliques in network analysis are defined as groups of nodes that all share common ties with one another. All nodes in the network are not required to be members of a group, thus this measure clearly identifies areas of high network inter-connectivity. The danger however, is that maximal density is a high standard for group identification and many elements that are strongly tied to a subgroup will be overlooked. Therefore, faction analysis combined with clique analysis is used to provide complementary views of both the large-scale and concentrated subgroups within a given network. It should be noted that subgroup analysis occurs after a large volume of qualitative learning has occurred in regards to the SESs the networks represent. This necessarily results in a high degree of reflexivity in defining subgroup analysis parameters and interpreting results. Rather than a negative aspect of the methodology, this reflexivity is given as a positive and required component in interpreting logical subgroup dynamics.

2.4 Results

2.4.1 Community A

In looking at the two-mode network results for Community A, a diffuse core-periphery structure can be seen in (figure 2.1). The core can be defined as the central region of the map where there is a visually apparent increase in connections between nodes. The periphery is visible as an outer ring around the core where nodes seem to share fewer connections. In this case, while that general structure is obvious, it is also clear that there is a slight division of the core, with a small clustering of nodes in the lower left. Centrality scores for code-phrases in Community A show "food," "positive," and "environment" (table 2.4) holding the top three rankings.

The graph in figure 2.2 illustrates the results from the subgroup analysis run for Community A. Trials of various faction divisions, beginning at 4 and working up to 12, showed a best match between quantitative fitness scores and qualitative researcher understanding of the network with a division of 9 subgroups. Clique analysis returned a total of 20 distinct groups of 8 nodes or larger (table 2.5).

2.4.2 Community B

It can be seen in figure 2.3, there is a shift in both the magnitude and relative position of the most central (table 2.6) code-phrase nodes in Community B relative to A. Yet the network itself exhibits the same general core-periphery structure. Looking closer it's possible to see the "positive" node sits fairly centered in the network, as it did in Community A. The "food" and "weather" nodes sit on opposite sides of it, again similar to Community A. However "weather" is a much more central node in this network and not associated with any real fracturing of the core as it was in Community A. Nor is it as closely positioned to the "negative" node as it was in Community A.

Figure 2.4 illustrates the faction and clique analysis for Community B. A faction division of 4 unique subgroups was determined to be the best fit between quantitative and qualitative network understanding. Eight cliques were found to be 10 nodes or greater in size (table 2.7) while over 30 were identified at the 8-node or greater size.

2.5 Discussion

Interesting relationships abound in all of the networks presented. Identification of specific SES relationships should be understood as a minimal subset of the potential SES information conveyed through this growing communication medium. It should also be remembered that my main purpose in this study is to explore the potential of using Facebook in SES studies by developing a reproducible methodology for doing so. Therefore, before looking into the SESs uncovered using this method I think two points are worth discussing in regards to the methodology in general. One is that there is a clear bias in the data-pull and data-processing procedures toward the deductive framework. The second is the strong centrality of the "positive" phrase in both community networks.

Every post collected through these procedures must, by definition, be connected to one of the four deductive code phrases. This is not true of the inductively derived code phrases. This places emphasis on the researcher defined knowledge system. I feel the main rationale for developing the hybrid deductive/inductive coding procedure is to help in translation between worldviews and resulting knowledge systems, this biasing of one view over the other in network measures deserves thought then. Obviously, this can potentially be viewed as a negative aspect of the method from the perspective of social equity between knowledge systems. Further result reproducibility puts influence on the researcher's individual understanding of the deductive filter. An alternative view however, and the one I hold, is that this actually allows one knowledge system a framework to more effectively understand another, and that a translation framework which connects the researcher's understanding of a system (through the deductive filter) to the lived experiences of those within in it (via inductive coding) is a primary requirement for information flow between knowledge systems. This methodology provides that framework through a network perspective, the deductive filter (researcher understanding), and inductive coding (lived experience). Thus, I argue that the deductive bias is a needed and desirable procedural element in order for the researcher to negotiate meaning from the lived experiences of system participants in a study-relevant context. I would also add, this is completely tied to researcher background and would lean toward whatever knowledge system the research employed rather than preferentially to one system. This is a very different than generic use of the "scientific method," which regardless of researcher background inherently favors scientific ways of knowing.

In many ways this method is formalizing the transactional communication process into a systems research framework. The identified sensitivity of the method to researcher interpretation of the deductive filter, and potential problems this could create for reproducing results between researchers is in many ways a question of shared system understanding between researchers. In larger projects than this one, where potentially multiple researchers are involved, a process of inter-rater reliability in shaping the deductive filter would limit inter-study reliability issues. External reproducibility is more problematic and would depend on the consistency of shared knowledge within the field doing the research. Either way however, this sensitivity puts limits on the where this method would be best applied, and most likely implies early application as a system scoping tool. I discuss in slightly more detail in the "general conclusion" of this thesis.

The high centrality ranking of the term "positive" aligns well with previous

Facebook studies of identity presentation (Zhao, 2008). It is considered that this result adds a qualitative factor of inter-rater reliability to the coding system used here. More practically, however, the dominance of this particular node in all of the networks allows it to act as a social marker in understanding other code relationships and a touchstone to compare network relationships between and within geographic communities.

Communities A and B experienced a series of extreme rain events throughout the early portions of this study. Looking at figure 2, posts in Community A related to “weather” are distant from those associated with positive expressions. Visual inspection hints that this weather event is likely the SES interaction around which the division in the core network occurred. Subgroup analysis supports this with a close affiliation of the code phrases “rain,” “negative,” and “weather” graphically and via faction analysis. Community B does not show this same separation between “weather” and “positive” phrases, or perhaps more importantly it does not show as close an association between “negative” and “weather.” To explore these relationships more fully it's potentially enlightening to turn toward each community network's connections to the “hunt” phrase.

Community A has a seemingly greater connection to the code-phrase “hunt” than does Community B, both in the order of its centrality ranking and its relative position to the touchstone phrase “positive.” The affiliation networks support this as well, again through the relative position of the “positive” phrase to “hunt” and faction analysis results. However, it's more striking in looking at the relationships between the “food” phrase and subsistence vs. store-bought items. Subsistence foods in Community A are much more central to Facebook conversations than in Community B, where the opposite is true for store-bought foods. This supports a tighter relationship to subsistence activities in Community A than in B. Interestingly, however, in Community B some of the most central posts (i.e. those with the greatest social reach) are indeed closely located to subsistence hunting-related phrases and clique analysis also indicates strong relationships between these types of nodes. A possible interpretation of these results is that subsistence harvest-based themes are strongly held ties in the community, despite perhaps a lessening relationship with them in everyday life.

Moving back to trying to understand what Facebook communication can tell us about adaptation responses to regional SES drivers, let's look more closely at the regional rain event that impacted both communities. Thinking about this, it's perhaps telling to consider the different relationships uncovered for each community around hunting. In Community A there is a relatively tight relationship to these activities and the response to the rain event was decidedly negative. Community B, on the other hand, does not illustrate as tight a relationship with hunting aspects of the network and the response was less negative. This could illustrate an increased vulnerability in Community A to changes in fall weather patterns that limit landscape mobility needed for subsistence harvest activities. Community B is seemingly less vulnerable to this type of event. Community B then may have a lower vulnerability to fall weather fluctuations than Community A, but at the expense of being more dependent on cash-based store-bought food.

Looking back at Community B's two-mode network, it is easy to see that “cash” and “negative” are closely located on the graph. This presents an interesting social dilemma. Further, clique analysis from Community B showed a close relationship between subsistence activities and positive expressions, potentially increasing social strain related to these competing life-ways.

This work makes no presumptions to judge these relationships, but it does make them clear in a way that might otherwise be difficult to perceive. The "reality" of these relationships will be uniquely understood by each individual in the community and the development of these networks should be used to frame conversations around them in order to illicit greater understanding and informed decision-making by those impacted. Additionally, as will be discussed in chapter three below, Community A experienced great built infrastructural damage during the rain event than Community B. The social ramifications of this may offer an alternative narrative to the one described above. This further emphasizes the scenario building potential of this methodology while simultaneously highlighting the need to use it in conjunction with more participatory methodologies for planning and management efforts.

2.6 Conclusion

The above discussion makes it clear that SES interactions are indeed communicated through Facebook conversations and are identifiable in an academically rigorous manner. A result that is no doubt unsurprising to anyone actively using this communication medium. Equally obvious to anyone familiar with this mode of communication is the difficulty of filtering through the huge spectrum of life experiences conveyed through it in order to arrive at any content specific understanding. A further challenge is placing these individual experiences in a broader community-based context meaningful to exploring SES interactions. The rewards of doing so however are substantial, as the medium provides unprecedented access directly into the lived social-ecological experiences of people as they perceive and value them. The methodology described in this work successfully overcomes these obstacles by, 1) spatially grounding a sample population, 2) using a researcher defined deductive code to filter through the vast quantity of posted content, 3) developing an inductive code to capture local understanding, and 4) using network analysis to examine system level relationships.

Additional questions remain, however. Future studies should be directed at understanding relationships between Facebook users and non-users within a given community, as well as relationships between Facebook posted content and instrumental environmental observations. Relationships between Facebook users and non-users are likely best examined through correlated interview and survey studies that identify user/non-user demographic and life-way patterns. Correlation with instrumental observations may be technically challenging depending on the specific environmental questions explored, however, "weather" related Facebook content compared to weather station data offers a relatively easy first approximation, at least in regards to this content, and will be examined in the next chapter.

Finally, this methodology is not envisioned as an end-product system-defining tool. Rather, I view this method best used as an exploratory technique to help shape research questions for further investigation and discussion with the communities involved.

2.7 Figures

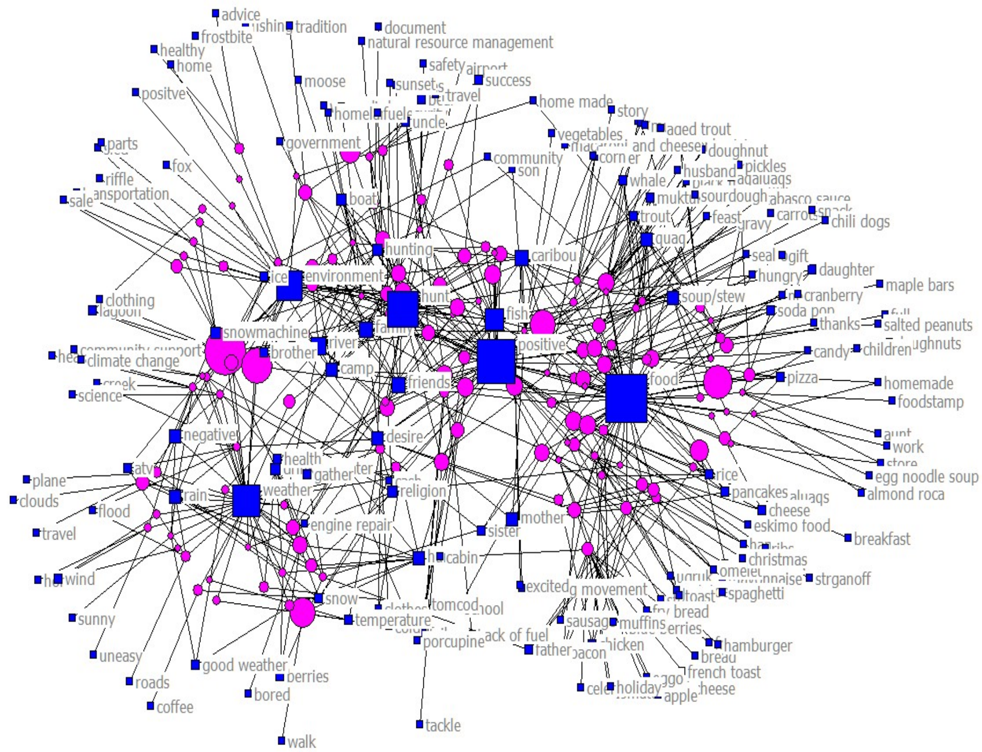

Figure 2.1 Community A Two-Mode Network Map. Community A: Two-mode network map illustrating a number of SES relationships. 1) The pink circles represent unique Facebook posts made during the study period. The size of these nodes is in relation to the degree centrality of these same posts in the Community A "people-to-post" network, as explained in the analysis section above. The blue squares represent code phrases associated with each post. Square sizes are indicative of code phrase degree centrality.

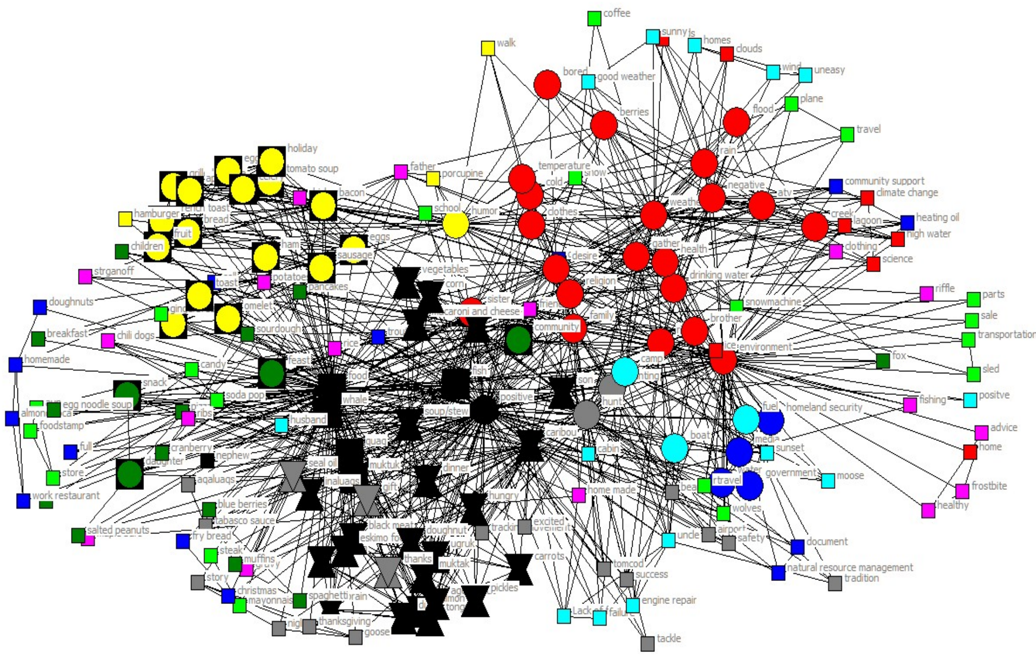

Figure 2.2 Community A Affiliation Network. Community A's code affiliation network. Colors indicate a forced faction division of 9 with a fitness of 3722. All cliques' sets defined for a minimum of 8 nodes per clique. Hourglass shaped symbols roughly in center of graph represent the combination of 9 highly overlapping clique sets (numbers 1-9 in table below). Boxed circles indicate grouping of cliques sets 10-12 in table below. And circles indicate clique sets 13-20 from below.

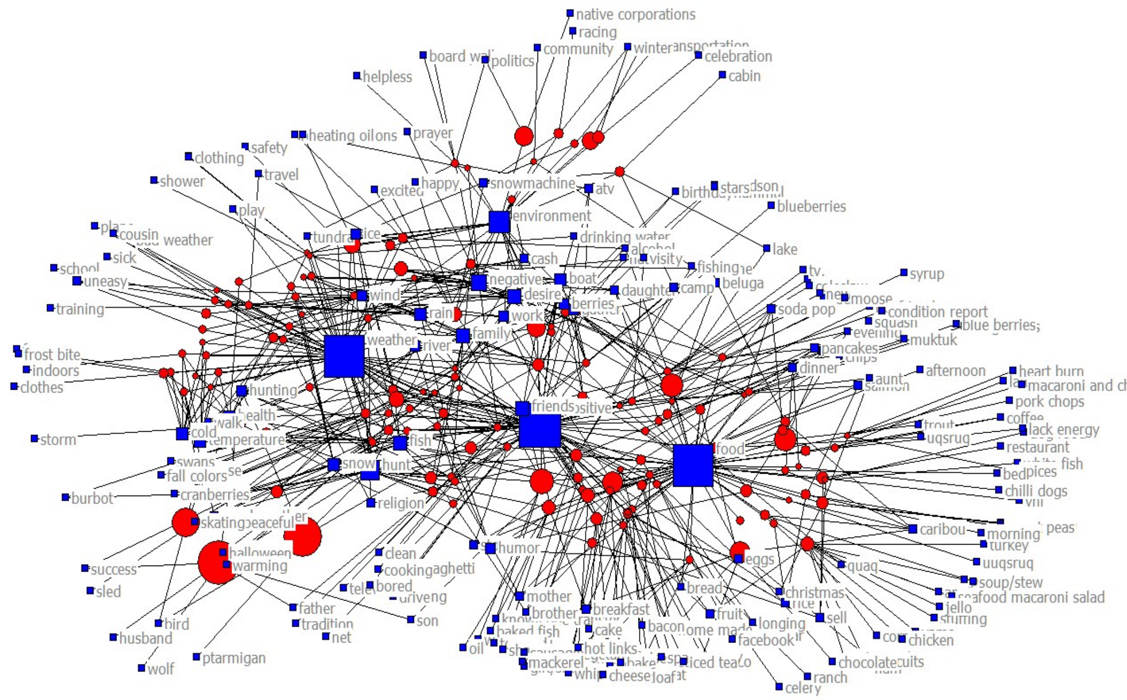

Figure 2.3 Community B Two-Mode Network Map. Community B 2-Mode network map illustrating a number of SES relationships. 1) The red circles represent unique Facebook posts made during the study period. The size of these nodes is in relation to the degree centrality of these same posts in the community B “people-to-post” network, as explained in the analysis section above. The blue squares represent code phrases associated with each post. Square sizes are indicative of code phrase degree centrality.

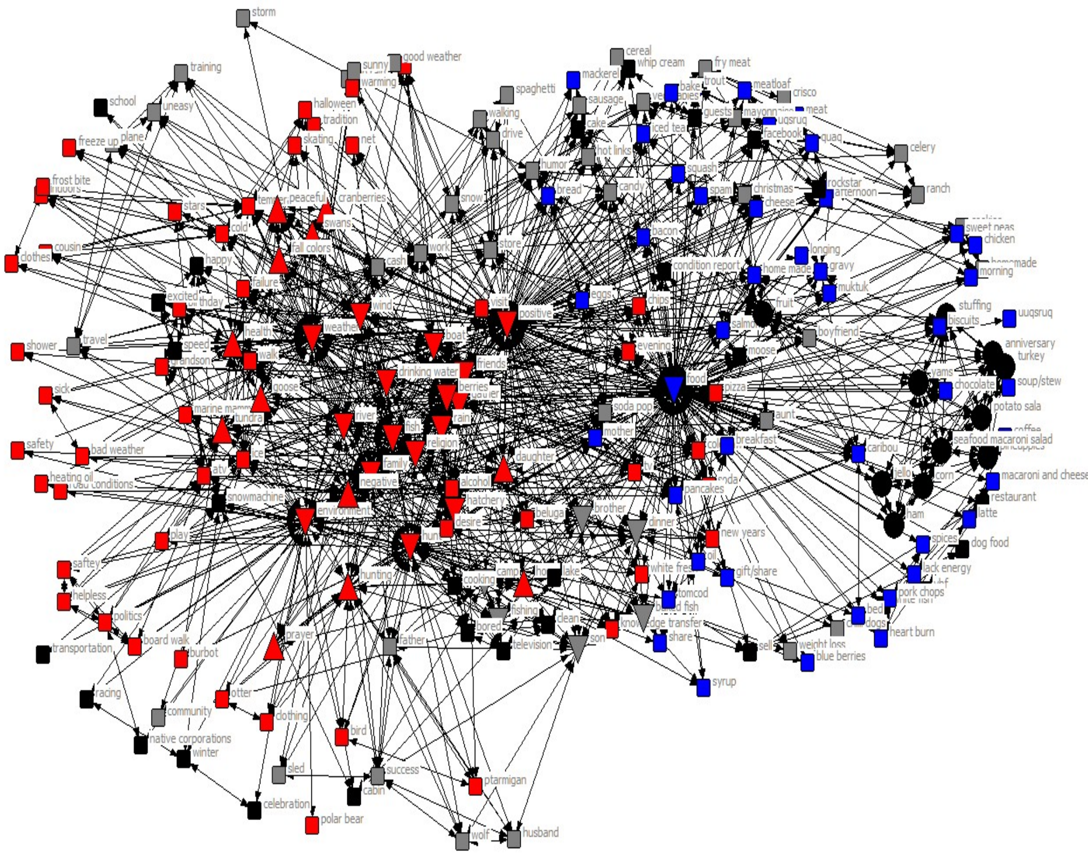

Figure 2.4 Community B Affiliation Network. Figure 2.4 illustrates the faction and clique analysis for Community B. A faction division of 4 unique subgroups was determined to be the best fit between quantitative and qualitative network understanding. 8 cliques were found to be 10 nodes or greater in size (table 7) while over 30 were identified at the 8 node or greater size.

2.7 Tables

Table 2.1 Community based Facebook Usage. Total community population in relation to self identified Facebook users. Percent usage is a minimum, as some community members are likely to use Facebook but for privacy reasons not divulge the community they are from.

Community	Public Facebook Users	Total Community Population	Percent (public) Facebook Users
A	109	374	29.00%
B	198	829	23.00%

Table 2.2 Deductive Code Table. Code phrases for the deductive framework with the general descriptions of content themes used to classify individual Facebook posts.

Deductive Framework	Description 1	Description 2	Description 3
Hunt	Posts that refer to hunting or hunting related activities where the connection is explicit (e.g. "fixed outboard, hunting tomorrow!")	Includes land and marine mammals, birds and fish	
Gather	Collection of plant resources	Berries, greens, etc.	
Food	Posts describing prepared food	Content shared about store-bought food	Content shared about the preparation of subsistence foods
Weather	Posts that directly refer to weather conditions (actual temps, wind speed, precipitation, etc.)	Content where weather conditions may be inferred (temperature from ice conditions, wind from cancelled/turbulent flights, etc.)	
"Environment"	Jobs related to working in the natural environment and/or tied to mixed cash-subsistence economy	Health and safety related issues	General miscellaneous category for posts that in some way reference environmental interaction

Table 2.3 Generalized Inductive Coding Rubric. Descriptions of content themes developed during the inductive coding phase. Specific phrases developed are illustrated in the network maps below.

SES Grounded	**Description 1**	**Description 2**	**Description 3**
Attitude	Positive-	Negative-	Neutral (or indeterminate)
Environment	Physical environment, (lake, lagoon, river, ocean, tundra, etc.)	Built environment (home, house, road, bridge, school, etc.)	
Relationships	Family (wife, sweetie, brother, bro, auntie, son, etc.)	Friends (bud, buddy, named-Joe, Danny, etc.)	
Possession	Have	Want/desire	Sell
Nutrition	Type- eggs, meat, muktuk etc., meal eaten at, occasion (holiday, anniversary, birthday, etc.)	Attitude- positive (thankful), negative, hungry, full, etc. Health implications (weight)	Store bought or "country" food (built or natural)
Hunt	Sharing, attitude, mode of transport, competing time constraints	Species, success (or not), camping, companions	
Weather	Good/bad weather (individual's interpretation of weather) positive/negative (individual's attitude, complaint, encouragement)	Drinking water (also shower, laundry, etc.) Health (mental, physical, illness, injury) Homes (unstable, at risk)	
Food	Recipes, trade, sell ingredients, share, family and/or social connection	Greetings- between friends, family	Humor (directed at mode of conv. i.e. "email me some")

Table 2.4 Community A Centrality List. Centrality scores for code-phrases in Community A.

Deductive/ Inductive Codes	Degree	Betweenness		Deductive/ Inductive Codes	Degree	Betweenness
food	0.403	0.348		trout	0.036	0.001
positive	0.360	0.311		rice	0.036	0.001
hunt	0.281	0.121		atv	0.029	0.003
weather	0.252	0.162		father	0.029	0.002
environment	0.230	0.172		brother	0.029	0.002
fish	0.137	0.026		temperature	0.029	0.002
river	0.101	0.017		ice	0.029	0.001
caribou	0.094	0.025		pancakes	0.029	0.001
friends	0.094	0.020		uncle	0.029	0.001
family	0.079	0.024		whale	0.029	0.001
humor	0.072	0.031		pizza	0.029	0.000
rain	0.072	0.006		success	0.029	0.000
desire	0.065	0.025		gather	0.022	0.002
camp	0.065	0.010		sister	0.022	0.002
negative	0.065	0.010		berries	0.022	0.001
mother	0.058	0.011		health	0.022	0.001
soup/stew	0.058	0.005		bacon	0.022	0.001
quaq	0.058	0.003		bear	0.022	0.001
religion	0.050	0.012		sell	0.022	0.000
snowmachine	0.050	0.010		soda pop	0.022	0.000
hunting	0.050	0.005		good weather	0.022	0.000
drinking water	0.043	0.004		lagoon	0.022	0.000
boat	0.043	0.001		daughter	0.022	0.000
snow	0.036	0.004		chicken	0.022	0.000
eggs	0.036	0.002		cheese	0.022	0.000
muktuk	0.036	0.002		wind	0.022	0.000

Table 2.5 Community A Cliques. Sets of code phrases that make up each identified clique for community A.

	Code Phrases in Each Clique
1	Positive family son caribou desire food soup/stew mother macaroni and cheese vegetables corn
2	Positive family caribou desire food fish soup/stew mother
3	Positive caribou food soup/stew ugruk inaluaqs mother eskimo food
4	Positive caribou food sister soup/stew seal oil thanks gift
5	Positive caribou food muktuk black meat soup/stew aged trout hungry carrots pickles doughnut
6	Environment positive family hunting hunt caribou desire food
7	Positive family hunt caribou desire food fish mother
8	Positive caribou food quaq brain tongue salmon muktuk oogruq duck black meat
9	Positive caribou food fish quaq whale muktak dinner
10	Positive food eggs cheese omelet ham sausage toast
11	Community food fish quaq muktuk whale daughter snack feast
12	Food eggs sausage french toast bread bacon fruit grilled cheese tomato soup apple eggo celery humor holiday
13	Environment water system media river government homeland security positive drinking water
14	Environment river positive hunt camp gather boat fuel
15	Environment river weather atv negative rain creek desire
16	River weather atv negative rain creek desire flood
17	Drinking water weather negative rain desire humor berries bored
18	Environment positive family weather hunting hunt desire brother
19	Positive family weather health sister religion brother clothes cold temperature
20	Positive weather health humor religion clothes cold temperature

Table 2.6 Community B Centrality Measure. List of top centrality measures for system component indicators in community B.

Deductive/ Inductive Codes	Degree	Betweenness		Deductive/ Inductive Codes	Degree	Betweenness
positive	0.423	0.333		daughter	0.035	0.003
food	0.394	0.396		cash	0.035	0.003
weather	0.394	0.229		caribou	0.035	0.001
environment	0.176	0.118		snowmachine	0.028	0.002
hunt	0.155	0.065		dinner	0.028	0.001
negative	0.106	0.034		rice	0.028	0.001
fish	0.099	0.022		soda pop	0.028	0.000
friends	0.092	0.022		candy	0.028	0.000
desire	0.092	0.015		sunny	0.028	0.000
family	0.085	0.018		uneasy	0.028	0.000
snow	0.077	0.003		camp	0.021	0.002
temperature	0.077	0.003		fruit	0.021	0.002
cold	0.070	0.002		religion	0.021	0.002
boat	0.063	0.007		atv	0.021	0.001
health	0.063	0.006		home	0.021	0.001
rain	0.063	0.006		breakfast	0.021	0.001
river	0.056	0.007		salmon	0.021	0.001
hunting	0.056	0.006		mother	0.021	0.001
wind	0.056	0.005		store	0.021	0.000
humor	0.049	0.006		beluga	0.021	0.000
ice	0.049	0.004		sell	0.021	0.000
work	0.042	0.006		home made	0.021	0.000
gather	0.042	0.004		eggs	0.021	0.000
berries	0.042	0.004		pancakes	0.021	0.000
				good weather	0.021	0.000

Table 2.7 Community B Cliques. Sets of code phrases that make up each identified clique for community B.

	Code Phrases in Each Clique
1	Boat positive friends gather berries food alcohol pizza coleslaw chips soda evening tv
2	Environment boat river positive friends gather family berries food weather fish
3	Environment river positive friends hunt gather family berries food weather fish
4	Environment boat river positive family food weather drinking water fish hatchery wind rain
5	Positive hunt food fishing camp dinner son brother baked fish religion
6	Food anniversary turkey stuffing ham pineapples seafood macaroni salad potato sala yams corn jell fruit
7	Environment hunt gather family home hunting berries negative daughter prayer
8	Positive gather berries tundra weather fish religion health goose cranberries swans fall colors peaceful

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Chapter 3:

Exploring Facebook Activity in Relation to Instrumental Observations

3.1 Abstract

Climate scientists, community planners, emergency management agencies, and natural resource managers can improve their understanding of locally scaled social-ecological system (SES) interactions by taking advantage of the diverse range of data publicly available on the social media website Facebook. However, it is important to establish a direct real-world relationship between Facebook activity and ecological conditions. In this study, I test this type of real-world interaction by comparing the frequency and content of weather related posts in Facebook to instrumental weather observations (precipitation, temperature, and wind speed) in two rural Alaskan communities. I compare data across two significant weather events: 1) an unusually heavy period of rain in August 2012, and 2) freeze-up, that same fall. Additionally, broader system dynamics are defined for each community in relation to weather conditions using a deductive-inductive coding and network development methodology. Network analysis is used to assess system changes contemporaneous with instrumental readings. Results indicate that Facebook activity changes in relation to changes in environmental conditions. Posting frequency increased around both rain events and freeze-up. Broader system changes were detected across each event, as well. I conclude that these associations establish a bridge to interpret Facebook data in relation to instrumentally recorded ecological conditions. Once this link is established, diverse and unexpected system interactions can be defined. I present an example of this for the two study communities. While these results are specific

to the case studies examined, I believe that relationships between Facebook activity and real-world environmental conditions are not. A diversity of systems need to be explored using methods similar to those I present in this study to establish the potentially wide range of social-ecological scenarios where a strong environmental component is present in Facebook communication. Some will be stronger than others. Where they are tightly coupled, the ability to conceptualize diverse system connections, aligned to ecological measures, and derived from lived experiences, illustrates the type of SES insights social media derived data can provide.

3.2 Introduction

Recent well publicized events like Hurricanes Katrina and Sandy have illustrated the tight coupling of social, technological, and environmental systems, spurring concern for how societies are adjusting to the very real local impacts of harder to see global change drivers, and raising interest in improved scientific understanding of social-ecological systems through the field of sustainability science (Lau & Kim, 2007). The concept of social-ecologic systems (SESs) is based on defining human-environmental relationships through the characterization of complex interactions between people and their environments. These interactions are composed of unique arrangements of feedback and/or reflexive mechanisms that occur across both geographic, temporal, and social scales (Cumming, Cumming, & Redman, 2006). Research and application of SES-based models attempts to identify and define these relationships within and across scales (Folke, 2006). There are, at a minimum, three fundamental concerns in the field: 1) how are rapid and persistent environmental change patterns impacting SESs, 2) what systems are vulnerable to what changes, and 3) how, or if, socially cooperative efforts can mitigate the negative impacts of critical system vulnerabilities. Specific issues around these concerns are approached with an aim to bolster overall system resilience, and/or promote strategic system transformation (Chapin, Kofinas, Folke, & Chapin, 2009). Social media can provide an unique insight into these systems by blending the observer's, or researcher's, deductive understanding of the system with the lived experiences of participants within the system (Estalella, & Ardèvol, 2007). However, this is only valuable if a direct link between ecological conditions and social media activity can be established. In this work, I explore the relationship between environmental conditions and social media dynamics for two rural northwest Alaskan communities (figure I.5 above) and use two regional weather events in the fall of 2012 as correlation tools.

3.2.1 Framing SESs in a Social Media Context

A good place to begin this conversation is by defining a few key terms, as I apply them to understanding SESs. I use a working definition of vulnerability similar to Adger's (2006) ideas that measure vulnerability as a function of "the state of (system) susceptibility to harm from exposure to stresses associated with environmental and social change and from the absence of capacity to adapt." I define adaptation, similar to Carpenter and Brock (2008), as the ability and/or process of a system to change in response to external forcing mechanisms. Important to understanding and characterizing SESs is the idea of resilience, which I cconceptualize as addressing the degree of change that a system can absorb without transitioning into something "new" (Folke, 2006). Transformation then occurs when a "fundamentally new system" develops with distinct and different social-ecological couplings than the previous system (Walker, Holling, Carpenter, & Kinzig, 2004). I frame my understanding of SESs around these definitions. System characterizations are based on identifying environmental change variables in conjunction with human response factors. Social media activity, specifically Facebook activity, is understood through this lens.

All social media content, particularly Facebook content, needs to be filtered to narrow the search for relevant information. This requires that the researcher develop a deductive understanding of the system of interest before formally collecting data. The details of this understanding will be variable depending on the specific system and scale being addressed, but in the case studies I am presenting here, I developed a filtering framework grounded in the locally important subsistence life-way.

3.2.2 System Background

Communities A and B are both predominantly Alaska Native and remote (Hamilton, White, Lammers, & Myerchin, 2012). The combination of these factors make a subsistence life-way extremely important both economically and culturally (Callaway et al., 1999). At a surface level subsistence can be defined as activities that promote the harvesting of life essentials (food, clothing, shelter) from the immediate landscape (Lonner, 1980). This is a simple, yet economically relevant definition due to the remote location of both communities and the associated high cost of shipping material goods into them. However, at the cultural level, subsistence is more difficult to define and incorporates concepts of both spiritual and material wellbeing (Case, 1989). I assume in this study that a subsistence life-way requires a high level of environmental awareness and that SESs grounded on subsistence activities will be tightly coupled to ecological components.

Specifically, I identify five broad system elements to use as a primary deductive filter in narrowing Facebook content. These are weather, hunt, gather, food, and environment. While the Facebook conversations identified using this filter covered many social-ecological connections, those around weather afforded the most interesting opportunity to compare social media activity to instrumentally defined environmental conditions. This is primarily because weather conditions have a direct impact on all five-system elements defined in the deductive code, and, instrumental weather data is easily available through the US National Weather Service archives with defined quality standards between locations. It is a good choice as well because weather related Facebook activity is fairly common in each community and therefore provided a sufficient sample set to assess.

However, the manner weather is discussed is variable and highly context-driven. Only certain contexts can be expected to manifest in Facebook data and those are likely to be based around unusual or socially important events. Instrumental comparisons need to be understood through these contexts. During this study, two key classes of social-ecologic events occurred that lend themselves to weather related instrumental comparison: 1) discrete storm events, and 2) the annual fall freeze-up.

Storm events during the study period involved the typical regional winter storms and a highly unusual period of intense rain in early fall. This rain event was significant and requires further explanation. In mid-August 2012 a persistent low-pressure system developed in the Chukchi Sea that drew in a series of moisture-laden storms across northwest Alaska. Some areas received as much as half their normal annual rainfall totals over the course of just a few weeks. National Weather Service hydrologist Ed Plumb was quoted in many statewide news stories describing it as “an extraordinary event, having this much rain over such a short period of time.” Plumb further elaborated that it was “kind of ironic, because the Wulik River had record low flows” earlier that summer. This type of extreme oscillation is beginning to be understood in reference to larger global drivers (Verboom et al., 2010; Lau & Kim, 2012; Wipf, Gottfried, & Nagy, 2013), increasing the importance of new SES tools, like the one I present here, to be developed and applied to emergent and highly localized system changes that are linked through larger scale system drivers.

The impacts of the persistent low-pressure system in the Chukchi Sea, and associated individual rain events, were regional in nature and all communities in the area were affected to some degree by it. The magnitude of the impact on individual communities was in large part based on the geographic setting of the community both in its position relative to the internal intensities of each storm and the physical properties of the community to withstand the event. Western communities, as well as those near the base of the Brooks Range, recorded greater precipitation totals than eastern communities or those further from the mountain front (National Climatic Data Center, 2013).

The physical characteristics of each community are important in how the storms impacted them, both from an ecological and technological perspective (i.e. built infrastructure). The relevant questions to ask in defining the physical characteristics for each community are divided along these two perspectives. Example questions are, “Is the community located on a flood plane or on a high bluff?” “Is it located on the tundra or more substantial foundations?” “What type of water and septic system does the community depend upon?” Or, “What types of waste management systems are in place?” As well as, “How vulnerable is the transportation and food system?” The answers to these questions combined with the internal storm properties help shape each community’s unique reaction to these unusual events.

The pattern of storm systems in August 2012 was sufficiently intense to be extensively covered by statewide news agencies. A review of that coverage clearly shows that infrastructural damage was extensive and that social systems were disrupted because of the storms. However, this occurred in a spatially discontinuous manner. Particularly, Community A at the Western edge of the impacted region and on a low lying barrier island, received considerable damage to its water system. Further, its waste management facilities flooded as well. This created social disruption, most visibly in a multi-week delay opening the K-12 school year. Community B is farther east and reported very little infrastructural damage. These factors undoubtedly play a role in the system dynamics I define in this work.

Unlike the unexpected storm events, freeze up is a socially significant, annually anticipated event (McNeeley, 2011). It marks a fundamental transition in the traditional seasonal rounds of the region (Fall, 1990). This has wide-ranging impacts in the way people interact with their environment and how they participate in subsistence activities. However, once again, there is considerable variation between communities in the details of these impacts. The differences are largely based on small-scale socio-ecological factors that shape the hunting, fishing, and gathering patterns of each community. Issues around freeze-up are often driven by landscape mobility issues and affect choices regarding which species to target and what technologies to use in doing so (McNeeley, 2011). Community A and B both depend largely on fishing as their dominant harvest resource. Both utilize, to one extent or another, marine and terrestrial mammals and each harvests a variety of tundra berries as their primary gathering resource (Moerlein & Carothers, 2012; Magdanz, 2010). Migratory birds are also harvested, but are not particularly relevant to the time frame of this study.

Landscape mobility impacts of freeze up are generally tied to a transition from boat and ATV use to snowmachine use. This opens up the landscape in most cases and allows greater mobility, improving the ability to access more distant terrestrial resources, namely caribou in the study region (Magdanz, 2010). However, the formation of ice limits the ability to fish with nets, and marks a switch to more widespread use of hook and line techniques. Additionally, freeze-up coincides with the rapid decrease in daily sunlight in high latitudes, a predictable environmental change that drastically impacts social activity within community. A late freeze could result in less opportunity to take advantage of increased landscape mobility for terrestrial hunting activities and socially important ice fishing, while an early freeze-up allows greater opportunities to participate in these activities before daylight hours and decreasing temperatures change opportunities. Naturally, an individual's relationship to freeze up is extremely complex and beyond the scope of what can be explained in this introduction, but it is clearly an important and anticipated event in the lives of community members from cold, high latitude environments.

Instrumental observation of weather conditions, and particularly how they change across long and short time frames, provide a socially objective view of environmental conditions. They result in certain, quantitative results that are easy to track and compare across time scales. Facebook research, linked to these results, can provide a form of "calibrated" social measures for exploring the reflexivity of social behavior and changing environmental conditions. The methods and analysis in this work test and define this reflexivity by comparing the frequency of Facebook posting activity to instrumental data. I assume that increased posting frequency that is instrumentally correlated to the two types of unexpected and expected weather events described above is an indication of Facebook-environmental condition reflexivity. Additionally, network analysis defined system adaptations and/or transitions around these weather events are also considered an indication of social media expression of instrumentally definable environmental conditions.

3.3 Methods

3.3.1 Data Collection

I used two primary sources of data in this study: 1) US National Weather Service records of daily high and low temperature, average wind speed, and precipitation (National Climatic Data Center, 2013), and 2) a census population of all public Facebook user-produced content in Communities A and B. Instrumental data was collected for each community from the nearest official US National Weather Service recording station and was retrieved from the National Climate Data Center archives. In one instance, the nearest weather station was located directly in the community. In the other, the nearest station was located approximately seventy-five miles to the west. Facebook data was collected using a deductive/inductive methodology designed to filter and assess social media communication based on researcher-defined parameters.

The method for retrieving usable data from a social media source such as Facebook is critical to the overall results. This process defines the boundaries for all systems that can be derived from the data, so it is important to understand the factors that affect it. Context is key, and a researcher must be aware of the reference frame they bring into the study as an initial required step. Next then, is to define a deductive framework for the system of interest. In my study communities, I built this framework around the subsistence life-way, and developed a set of clear themes: weather, hunt, gather, food, and environment that I used to filter Facebook communication (see table 2.2 above for more detailed definition on these themes). This is necessary because the richness of communication on Facebook allows, perhaps even encourages, the sharing of large volumes of diverse personal and social experiences (Lampe, Ellison, & Steinfield, 2007), many of which are not at all, or only very distantly, related to my research interests. A deductive framework has to be in place to allow filtering of this information into understandably discreet packets. This framework needs to be explicit to allow the researcher's biases to remain visible throughout the research project. Changing the deductive framework is all that is needed to address a wide variety of research questions. The filtering process is concluded by analyzing the public wall content of each community user during a defined timeframe and collecting all content that fits the deductive framework.

Collected content is then coded through an inductive process to define SES components from the shared communication of Facebook users. The inductive code is developed by capturing key-word style terms directly from raw user-generated posts. More than one code can, and usually was, associated with each unique post. The relationships between the deductive and inductive codes act as a bridge between individual-community level social-ecological perceptions and broader SES concepts in sustainability science. The relationships between the deductive and inductive codes can be seen in the networks below and will be described in detail in the analysis and results sections.

Finally, social network data was collected from all saved content to explore the social reach of each post and associated coded themes. Fellow Facebook users who either commented or liked a specific post were identified. The content of these user's posts was not assessed, however, to respect potential privacy issues. The date and time of each post was also collected. These basic procedures of developing a system-based deductive code, filtering social media content based on it, then developing an inductive code, and finally recording the social and meta data for each piece of content can be adapted to a wide range of research questions simply through adjusting the original deductive system framework.

3.3.2 Data Analysis

Analysis was conducted in a two-step process. First, posting frequency and content were compared with instrumental data to identify whether or not patterns of Facebook activity could be tied to instrumental trends. Second, network analysis was used to develop a quantitative tool for assessing changes in code-phrase relationships around instrumentally defined weather periods. I assume code-phrases represent first-approximation system components and so this step is really acting as a proxy for identifying system changes aligned to environmental conditions. During this step, Facebook content was divided by posts made prior to freeze-up and posts made after freeze up for each community. Freeze-up was instrumentally defined as the first day the daily high did not cross the freezing point. Defining freeze-up at this point has precedent, as it aligns well with modeling parameters designed to determine freeze-thaw days under varying climate scenarios (http://www.snap.uaf.edu/data.php).

A number of network analysis measures were taken to define system changes before and after freeze-up. The first used a hybrid two-mode network construction to compare the centrality of content phrases to the social reach of individual posts. The next looked at the centrality of code-phrases when direct relationships were compared between them, based on affiliation within individual posts. A third set of measures examined subgroup formation between code-phrases. The combination of these measures allowed system changes to be identified and considered in relation to instrumental observed environmental changes. Critical to this process is defining the ecological thresholds across which system changes are sought. Clearly, many thresholds will not register via social media channels. This type of real-world check serves as an early indicator of whether or not the SES of interest is appropriately approached via social media research methods.

3.4 Results

3.4.1 Community A

Community A posting frequency results can be seen in figure 3.1. Two pulses of increased activity can be identified. The first occurs immediately following two of the highest precipitation events. The second happens right around the time that maximum daily temperature crosses the freezing point on October 10, 2012. The deductive-inductive codes for each day's Facebook posts can be seen in table 3.1 alongside corresponding instrumental observations. The content of the inductive codes is the most interesting. Prior to freeze-up, the content clearly identifies the rain events in August and September. Just before October 10, content shifts to discussions of lowering temperatures. Freeze-up is marked by a pulse of snow-related content that aligns to both temperature and precipitation records. A mid-December wind event can be seen via Facebook content and substantiated by average wind speed recordings. Later in December a cold snap is equally registered via Facebook and substantiated through instrumental observations

The two-mode networks before and after freeze-up in Community A are visualized in Figures 3.2 and 3.3. The “before” network has a split core-periphery structure. The split occurs around the deductive code hunt on one side, closely associated with the inductive positive code-phrase, while weather and negative form a mirror image deductive-inductive pairing on the other side. The degree centrality of posts tied to the hunt code-phrase are larger than those connected to weather. Post freeze-up, the network collapses into a single core-periphery structure.

Table 3.2 illustrates the relative degree centrality rankings for the top twenty code-phrases in each network. The before network shows weather is ranked highest followed by hunt. Rain and negative are highly ranked as well. The after network indicates that rain and negative completely fall from the list, while food enters and shifts immediately to the top.

The content shifts between the before and after networks are seen in the sub-group analysis, as well. Figures 3.4 and 3.5 illustrate the combined results for both faction and clique analysis. Faction analysis results for the before network show four meaningful sub-groupings. While it is much harder to derive meaningful sub-groups for the after network, a faction count of five was eventually settled upon. However, node groupings are not spatially clustered and I have little confidence these identifications represent real-world sub-groups. Tables 3.3 and 3.4 list the respective before and after clique sets. The before clique sets show strong subgroups forming around the rain event. These sub-groups are heavily bound to negative social emotions. After freeze-up clique sets show a return to a more positive association with weather interactions.

3.4.2 Community B

The frequency posts for Community B are reported in Figure 3.6. There is an interesting gap in posts during the month of November. This will be discussed momentarily. Additionally, there are a greater number of posts in Community B than A. This is an expected background noise caused by the larger size of Community B. However, prior to freeze-up, increased pulses in Facebook posts marked three of four precipitation events. Similarly, freeze-up itself can be identified by an increase in Facebook communication traffic with daily high temperatures dipping below freezing. Following freeze-up, weather related Facebook activity drops to zero. Data collection issues could be the cause of this result, or it could represent a period of no weather related Facebook communication. The likelihood and implications of both scenarios will be addressed below. During this time, temperatures steadily declined, there are three to four wind events, and little precipitation. After this period of low activity, posting kicks up again. This falls in line with a large wind and precipitation event, which is followed by steadily warming temperatures through the end of the study period.

Table 3.5 illustrates the deductive-inductive code results for Facebook posts compared to instrumental data. Prior to freeze-up the pulses of posting activity seen in figure 3.6 are reflected in pulses of content diversity. These occur in relation to instrumental data in two general positions during an event, or after. The first is during a precipitation event, where posts tend to include the code-phrases negative and rain. They also tend show a variety of individual coping phrases unique to each post. The second is after a precipitation event. These posts include the phrases positive and peaceful and relate to activities out on the landscape to a much larger degree. Similar to Community A, the lead-up into freeze-up is marked by steadily falling high temperatures, below-freezing nights, and a pulse of Facebook content taking note and responding to the dropping temperatures. Another pulse of content centered around ice conditions marks freeze-up on Facebook and is tied to conversations around the wind conditions. Instrumentally, high winds are recorded at this same time with little precipitation, and high temperatures drop below freezing. Following the gap of inactivity in November, the volume of Facebook content ramps back up. Instrumentally this is a period of cold, dry, relatively calm conditions. Facebook posts reflect a desire for snow and an awareness of the cold temperatures. This calm period is broken by a blizzard event of snow, high winds, and a general warming. Facebook content tracks this change with weather observations and nuanced reflections on the mixed relationship residents have with winter storm events.

Before and after two-mode network maps can be seen in Figures 3.7 and 3.8, respectively. The before network does not have as distinct a division within the core as Community A. The after network is much larger but otherwise has a fairly similar core structure as the before network. Content differences between the before and after network seem to be based on a greater diversity of individual inductive code-phrases centered around common themes rather than sweeping differences in the overall tone of content. Table 3.6 shows the degree centrality ordering of the top twenty code-phrases in each network. The before centrality order has weather, positive, and negative grouped at the top, rain is ranked fourth, and a selection of land-based subsistence activities round out the list. Like in Community A, food is the most central in the after network. Unlike Community A, weather does not drop to the bottom of the list but stays closer to the top. Ice-based subsistence activities enter the bottom half of the list instead.

The results of sub-group analysis are presented in figures 3.9 and 3.10, and tables 3.7 and 3.8. The before network was divided into four factions and six cliques. The after network was divided into five factions and five cliques. Again, the before network was fairly easy to divided into logical factions while the after network resulted in scattered groupings across the breadth of the network. Clique analysis in the before network pulled out four fairly distinct groupings radiating out of the core of the network with considerable overlap in the center. The after network showed less diversity in clique membership and considerably more overlap in the core.

3.5 Discussion

Community A weather related posting frequency spiked during instrumentally measured weather events. This is exactly the type of communication behavior expected if Facebook conversations are based on real-world conditions. The inductive codes associated with these posts also track to instrumental markers; rain is mentioned when precipitation is recorded, temperatures are discussed when instrumental readings suggest important changes in temperature, etc. Given the frequency and content alignment with instrumental readings, there can be little doubt that Facebook conversations typically report “actual” weather conditions. In the results, key patterns are identified; the unusual rain events, freeze-up, etc. However, not all of the instrumentally identified events are discussed. Specifically, many instrumentally recorded fluctuations in wind speed, which instrumentally seem significant, do not coincide with changes in observed Facebook activity.

The net effect of this posting pattern is that Facebook conversations seem to accurately record weather conditions, but they don't record all types of conditions equally. While there is a general background chatter of weather related content, much like in everyday face-to-face conversations, it is the socially significant events that substantially register via Facebook. What defines significance can be based on the extreme or abnormal quality of the event (i.e., the extended period of rain) or something more normal but anticipated, like the annual freeze-up. Non-participatory Facebook investigations then, like the example I have provide here, can identify locally important environmental change events but likely are not well suited to study daily environmental conditions.

The network analysis of Facebook conversations for Community A before and after freeze-up show a distinct split in the core of the network around the rain events prior to freeze-up. Then a collapsing of the network into a single unified core after freeze-up. Before freeze-up the split core seems to revolve around, on one side, a positive community relationship with hunting and related subsistence activities (gathering, time with family and friends, etc.). On the other, negative feelings are tied to the weather, specifically the rain, and coping mechanisms like humor and religion can be elicited along with concerns for other aspect of life that the rain is affecting, pointedly the community water system. A possible narrative derived from these associations ties community wellbeing to subsistence activities and points to a vulnerability to fall time fluctuations in weather patterns that impact them. The ability to fully define the mechanisms of this vulnerability, in terms of duration of exposure, degree of harm, and ability to adapt is beyond the scope of this type of research tool. However, the clear association of a negative social reaction to the unusual rain events and positive associations connected to subsistence activities should can serve as a guide to focus more specific research aimed at defining and testing the mechanisms linking the two different sets of positive and negative associations. And clearly, the negative ties connected to weather in this network-based system open the door to start looking at concepts of vulnerability based on conceptions of harm tied negative perceptions. Observation-based social media research tools are well suited for developing this type of exploratory system understanding, but need to be supported by participatory methods to more fully understand identified connections. Observation-based system conceptualization, like this one then, are best suited to create a “base map” for more focused, integrate, and diverse research efforts.

I interpret the collapsing of the split core after freeze to be representative of a return to more normal, that is socially expected, environmental conditions. I also believe it represents a seasonal system-wide transition triggered by temperatures dropping below the freezing point. As expressed by the Facebook community, this transition is marked by communicative activity switching from topics framed around subsistence harvesting activities to in-the-home food and family themes.

Community A's extensive infrastructure damage needs to be considered as well when interpreting the before freeze-up system. While Facebook conversations around this issue, including the delayed start of public school, do not make a large impact in the Facebook network, it is likely that the combination of both infrastructure damage and subsistence impacts increased the negative association with the rain events. However, based on the large social influence of posts related to subsistence, and much smaller reach of posts connected to infrastructure damage, it's clear that subsistence topics resonate more powerfully in the community, as expressed via Facebook. Given that, it's maybe not surprising that impacts to subsistence themes would be discussed more socially, while infrastructure issues might be handled more formally through different communication channels (e-mail, phone, face-to-face) than examined here. This is an example where the integration of additional research methods would certainly be needed to improve overall system understanding.

The narrative in Community B is a bit different, but there are a few issues in the results that need to be discussed prior to exploring the differences between communities. The first, and most obvious, is the large gap in weather related data through the month of November. There are a couple of possible explanations for this. First is simply a flaw in the data collection methodology. Data collection requires scanning every post of every user in the community during the study period. I did this on two-week intervals, in real time, as external events unfolded. Due to the technical functionality of Facebook at the time, there is a possibility that if a large volume of posts were made during any given two-week period, some content may not have been viewable during the next data collection effort. While possible, this seems unlikely since it is only the weather related posts that are absent. In other words, posts related to the other deductive codes (hunt, gather, food, environment) became less frequent, but do not disappear completely during this time. If this were a study implementation flaw, all of the content would be expected to be absent.

Another possibility is that the weather was just not discussed during this time frame. Supporting this idea, Community A also had a marked decline in weather related content during this period. This makes some narrative sense as will be discussed below. Most likely however, a combination of the two explanations is at fault. Either way, there is no real way to go back and determine exactly what happened, since any missing post would be difficult to find at this point. This lack of ability to go back and cross check data at a later date is a methodological flaw that needs to be refined in future works.

However, like in Community A, Community B posting frequency and conversational content track well with instrumental observations when present. Pulses in posting frequencies in Community B captured three of four distinct precipitation events, the transition through freeze-up, and a blizzard in early December. The marking of these events is similar to Community A, which illustrates their regional nature. This, as in Community A, clearly indicates a feedback between Facebook activity and instrumentally defined weather conditions.

What is different is the social response to these events as interpreted by building a scenario-based narrative around the network analysis results. This is one of the benefits of using Facebook as a research-scoping tool; the ability to correlate regional social-ecologic events between communities and then identify distinct system responses at the local level. The differences in cross-scale dynamics can then guide further investigations by acting as a framework for developing research questions through generating a variety of scenarios to explain, then test, causative mechanism for cross-scale system relationships.

The two-mode network analysis for Community B prior to freeze-up does not show the same split-core structure as seen in Community A. The weather code-phrase prior to freeze-up is also not as closely positioned to the negative code-phrase and is more closely situated to the positive code. The unusually long and heavy period of rainy weather is certainly noted in the network, as can be seen in the high centrality rankings of weather and rain code-phrases, but absent in the top of the rankings are codes tied to subsistence harvest activities. This is different than in Community A, where subsistence proxies rank high in the centrality table.

A narrative can be constructed around these results that might imply Community B's fall subsistence activities were not as physically impacted by the rain events as those in Community A. A number of reasons can be identified to explain this. First, perhaps, the subsistence patterns in Community B depend more on winter, spring or summer harvesting than fall harvesting. Second, maybe they simply do not have as tight a physical tie to subsistence activities as Community A does. Socially they certainly do, as the social reach of posts relating to subsistence themes are the highest in the network. This was true in Community A, as well. It is also very possible that the lack of infrastructure damage in Community B simply made the rain seem less important. Though if that were completely the case, it should be expected that subsistence related code-phrases would still have ranked high in centrality, instead of only the negative phrase ranking lower. Either way, the indications are that Community B is less socially vulnerable to fluctuations in expected fall weather patterns than Community A, based on the decreased relationship between weather and negative code-phrases. Once again, this is only a broad and preliminary defined application of system vulnerability, and grounded on the implied component of “harm” that is attached to the code-phrase negative. While not fully developed, I suggest this is a close proxy to Adger's (2006) concepts of vulnerability in such that it is an indication of social perception of exposure to harm, but concede it says little about the system's ability to adapt. An interesting question that then develops is, "To what extent is this decreased vulnerability associated with variance between communities and their relationships to subsistence activities as opposed to social perception of infrastructural vulnerability?"

After freeze-up results support the differences in social vulnerability between communities being strongly tied to subsistence relationships. Both communities show that food related phrases rise in centrality after freeze-up. However, looking at the details between communities, it can be seen that Community A food relationships are more closely tied to subsistence-based foods, while in Community B there is a greater association with store-bought foods. I interpret this as an indication of greater utilization of subsistence resources in Community A than B, but it is a limited interpretation bounded by the limits of the data source defining the system. These limits are primarily enforced by the distribution and social reflexivity of novel individual experiences in the community in relation to who is active on Facebook and who isn't. The deductive code used to originally filter Facebook content also places limits on the degree of certainty that can be placed on system interpretations.

Clearly, there are other possible narratives that can be developed to explain the differences in network results. However, with the given goal of this work to examine the potentiality of using Facebook in SES-based research, what is critical is that both community networks identified regionally shared environmental experiences, that are instrumentally corroborated, and are able to be further assessed to identify locally specific responses. This allows for inductively developed cross scale SES models to be developed. These models are ideal for focusing and contrasting against further work aimed understanding and addressing system vulnerabilities, which makes this form of social media research an ideal SES project scoping tool.

3.6 Conclusion

My intent in this study has been to establish a connection between communication activity on the social media website Facebook and real-world ecological or environmental conditions. I set about doing this by looking at the Facebook activity of two communities that are regional neighbors in remote northwest Alaska. These communities were selected as case studies because of their strong relationship to subsistence life-ways and a developed communication infrastructure sufficient to support local social media use. I assumed that this particular life-way, combined with social media access, would allow for an environmentally attentive study population likely to converse about ecological relationship as part of their regular social media routine. Based on these assumptions, and a general SES perspective, I developed a systems-based deductive framework to filter social media content and define important ecological relationships. I selected weather related content as suitable for testing social media activity for direct linkages to environmental conditions. I made this choice namely for the normative power of instrumentally collected meteorological data to compare weather conditions across scales, and defined two types of weather events that I anticipated to register via social media activity. These were highly unusual or odd events, and predictable, but highly anticipated events. The degree to which these events were reflected in social media behavior was defined as a function of posting frequency and content alignment with instrumentally recorded conditions.

Over the course of the study period both types of events occurred. An unusual moisture pattern developed over the region that early in the study sent a series of intense rainstorms across the region, causing locally relevant infrastructural damage. Later in the study period, the socially important ecological transition from liquid to frozen water occurred. In both instances, increased posting frequency and weather aligned content changes were documented in Facebook activity. This clearly answers, in the affirmative, the primary study question of whether or not social media activity can be correlated with real-world environmental conditions.

This conclusion holds only within limits however, and results showed that some types of environmental information, namely conditions that are likely to be socially perceived as mundane or normal, do not seem to register via day-to-day social media use. An example of this is the many large fluctuations in wind speeds that were instrumentally recorded, but rarely remarked upon in Facebook. Another limitation is the deductive framework used to filter down the volumes of social media content produced in each community to manageable, relevant, forms of usable data. This is necessarily created based on the researcher's own worldview and preliminary understanding of the system of interest, with little or no initial input by system participants. If the researcher poorly understands the system to begin with, data loss through poor filtering is likely to create poor results.

The deductive framework, however, is a very import part of the process for incorporating social media content into a broad range of SES understandings. In order to adapt the methodologies I describe here to address a diversity of other human-environmental interactions, specific SES questions or issues, a researcher need only adjust the deductive framework to their research area. Then follow basic structure and system-dependent reasoning for how inductive codes are developed and network analysis is deployed. System dynamics then, can be interpreted based on combined researcher and participant identified relationships.

This type of research produces ideal results for developing and testing network-based scenarios and system models ideal for follow up, focused research that includes a diversity of methodologies. Future work needs to establish the range of SESs that are applicable to address using social media methods, as well as, complimentary social and natural science methodologies useful to expand social media-based findings.

3.7 Figures

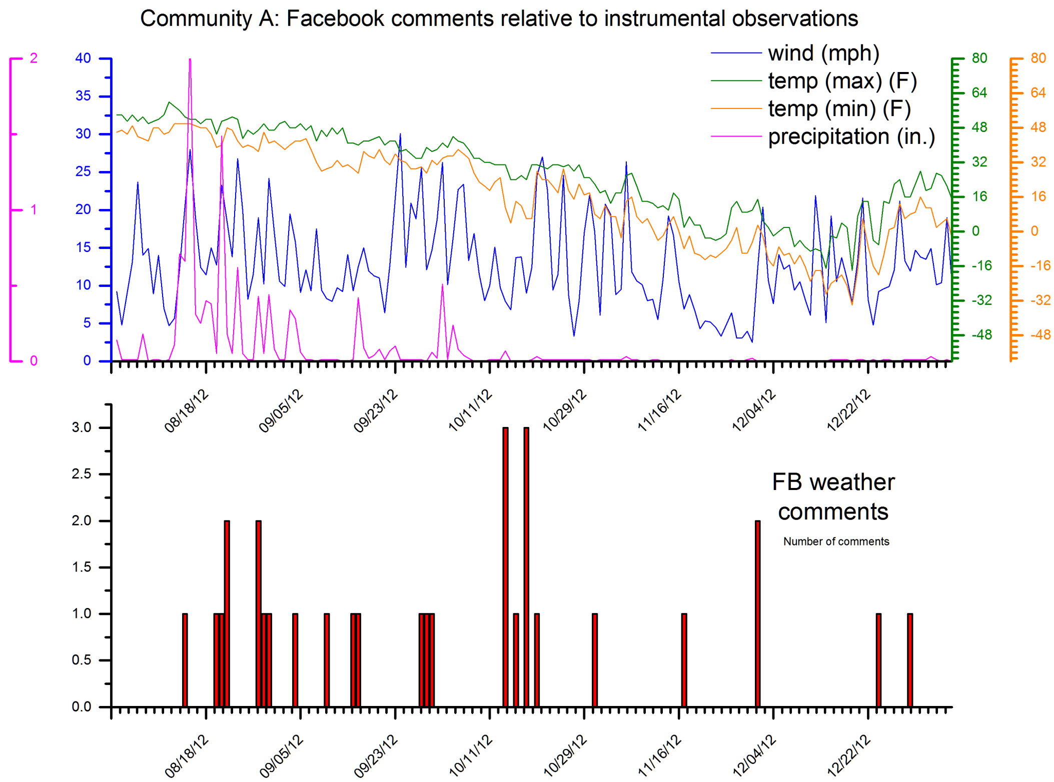

Figure 3.1 Community A Posting Frequency to Instrumental Data. Community A instrumental data in relation to weather specific Facebook posting frequency.

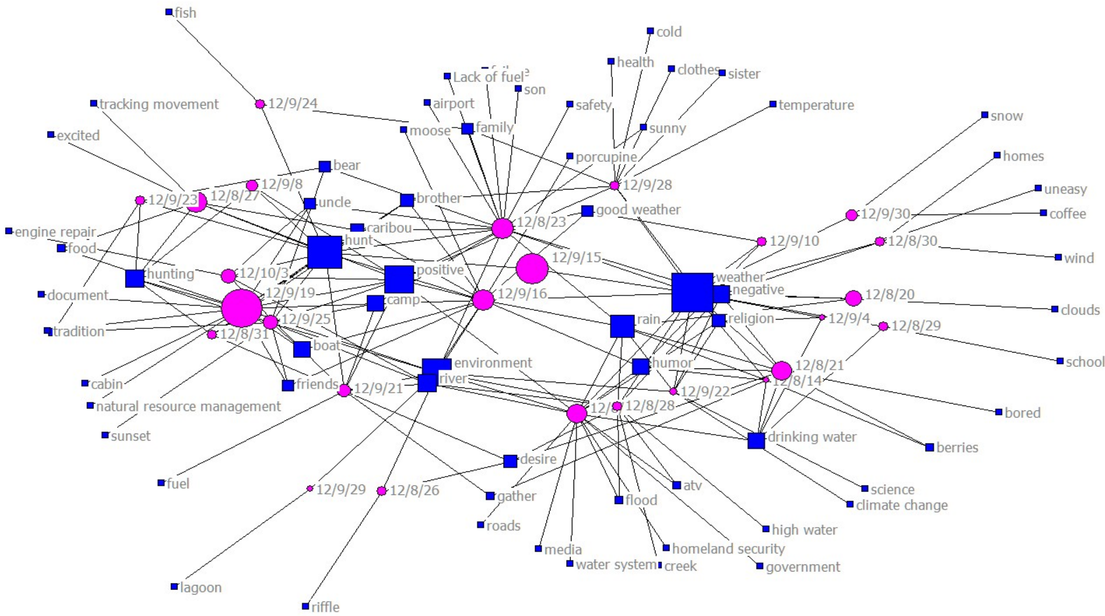

Figure 3.2. Community A Two-mode Network Before Freeze-up. 1) The pink circles represent unique Facebook posts made during the study period. The size of these nodes is in relation to the degree centrality of these same posts in the Community A "people-to-post" network, as explained in the analysis section above. The blue squares represent code phrases associated with each post. Square sizes are indicative of code phrase degree centrality.

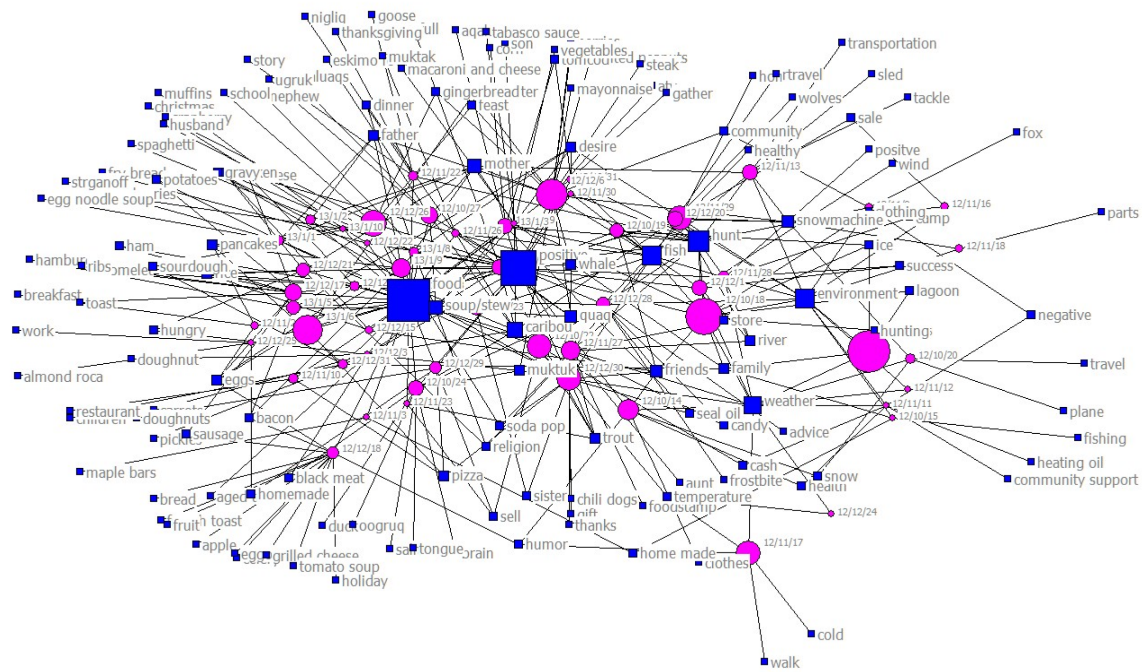

Figure 3.3 Community A: Affiliation Network After Freeze-up. 1) The pink circles represent unique Facebook posts made during the study period. The size of these nodes is in relation to the degree centrality of these same posts in the Community A “people-to-post” network, as explained in the analysis section above. The blue squares represent code phrases associated with each post. Square sizes are indicative of code phrase degree centrality.

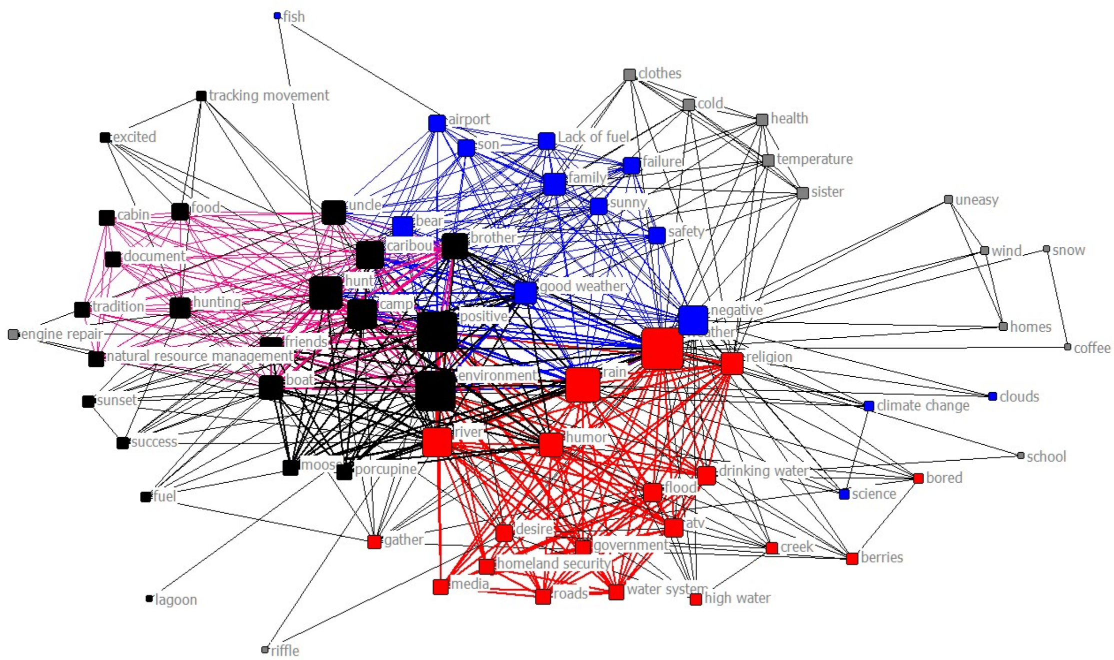

Figure 3.4 Community A Affiliation Network Before Freeze-up. Color of nodes represent faction membership. Tie colors are indicative of cliques' groupings.

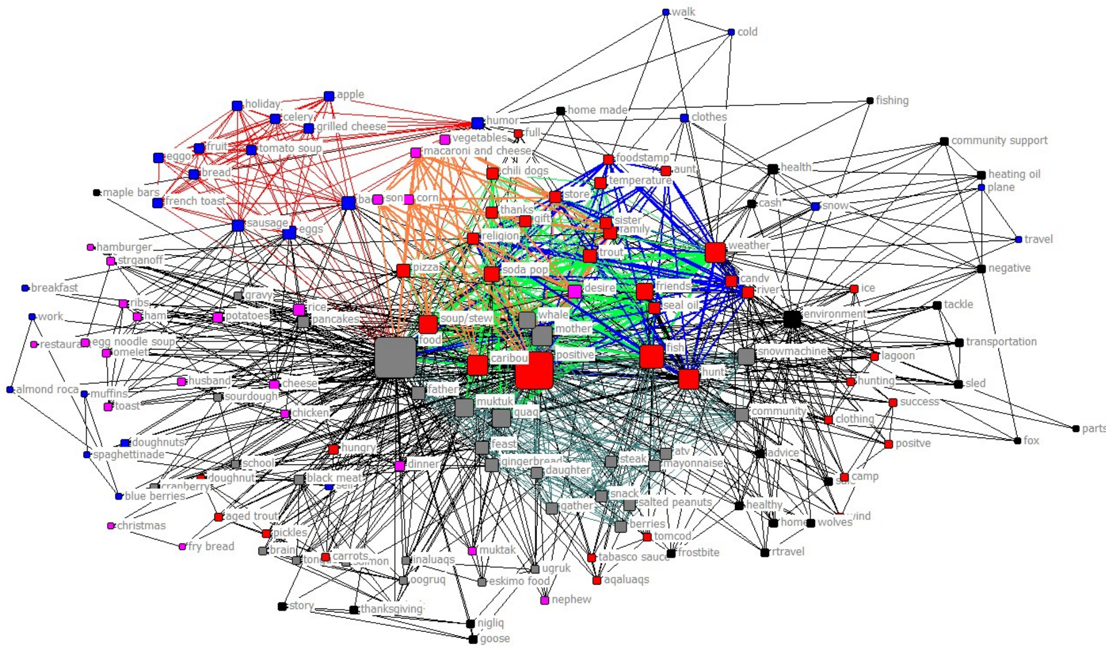

Figure 3.5 Community A Affiliation Network After Freeze-up Color of nodes represents faction membership. Tie colors are indicative of cliques' groupings.

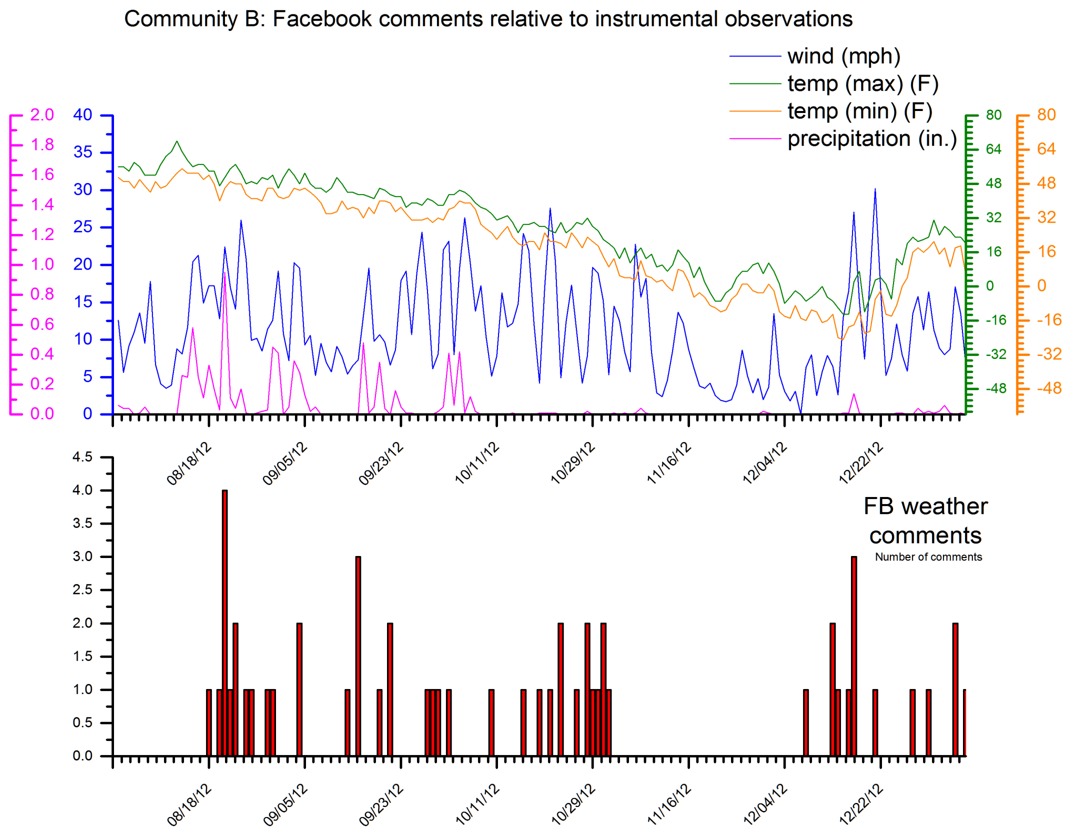

Figure 3.6 Community B Posting Frequencies to Instrumental Data. Community B instrumental data in relation to weather specific Facebook posting frequency.

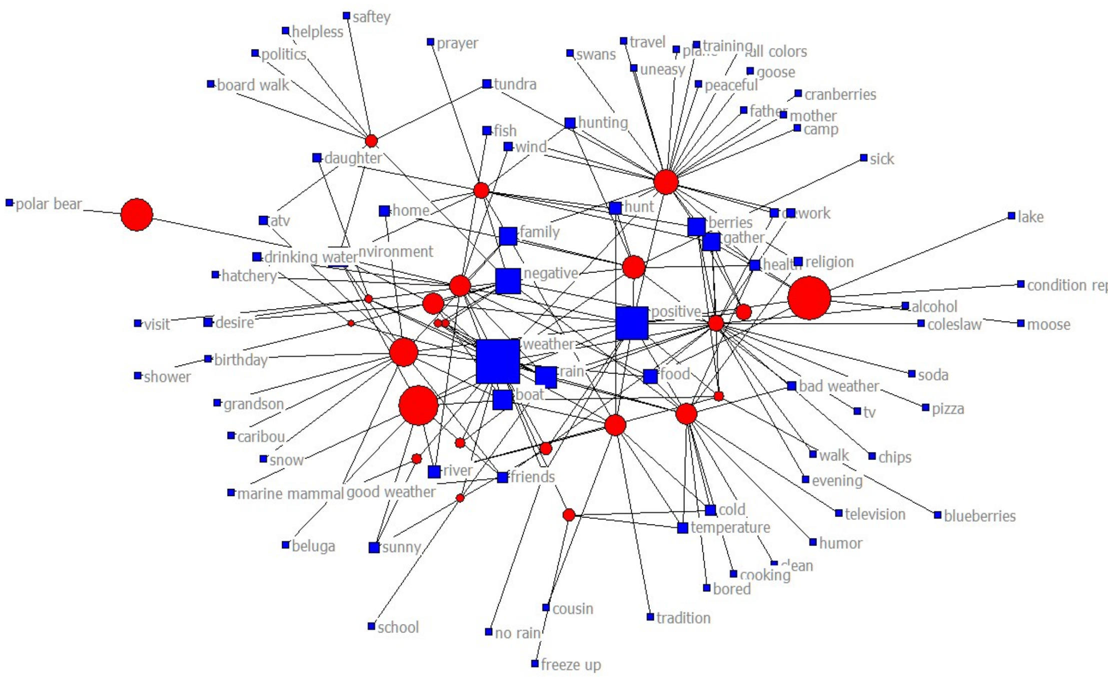

Figure 3.7 Community B Two-mode Network Before Freeze-up. 1) The red circles represent unique Facebook posts made during the study period. The size of these nodes is in relation to the degree centrality of these same posts in the community B “people-to-post” network, as explained in the analysis section above. The blue squares represent code phrases associated with each post. Square sizes are indicative of code phrase degree centrality.

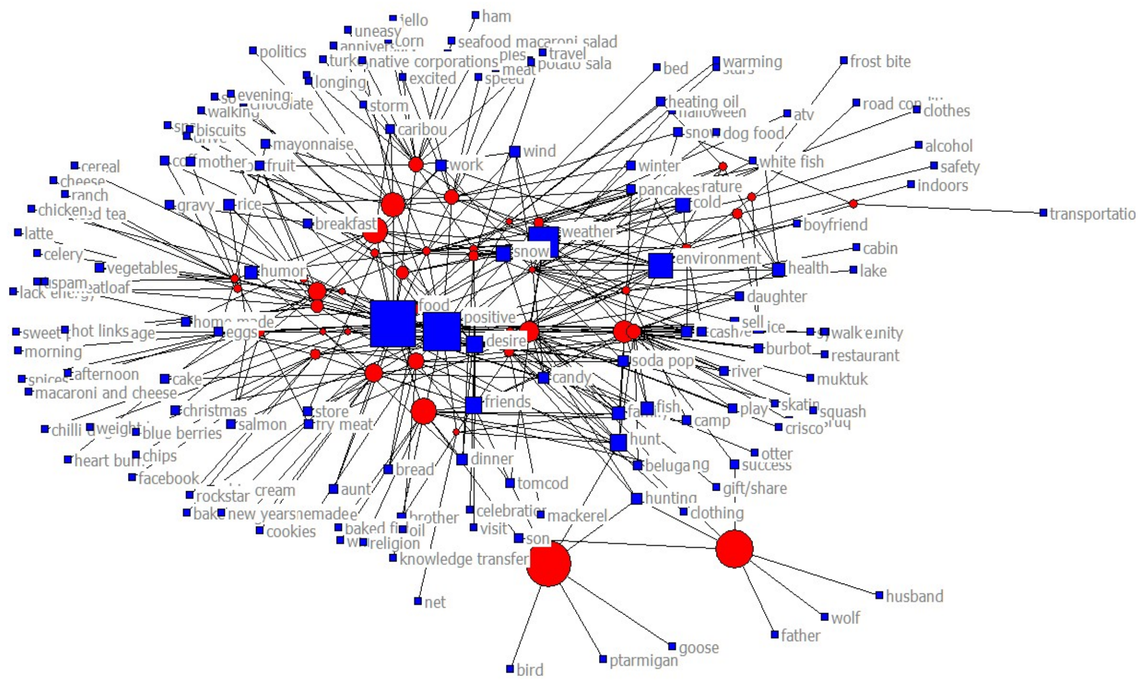

Figure 3.8 Community B Affiliation Network After Freeze-up. 1) The red circles represent unique Facebook posts made during the study period. The size of these nodes is in relation to the degree centrality of these same posts in the community B “people-to-post” network, as explained in the analysis section above. The blue squares represent code phrases associated with each post. Square sizes are indicative of code phrase degree centrality.

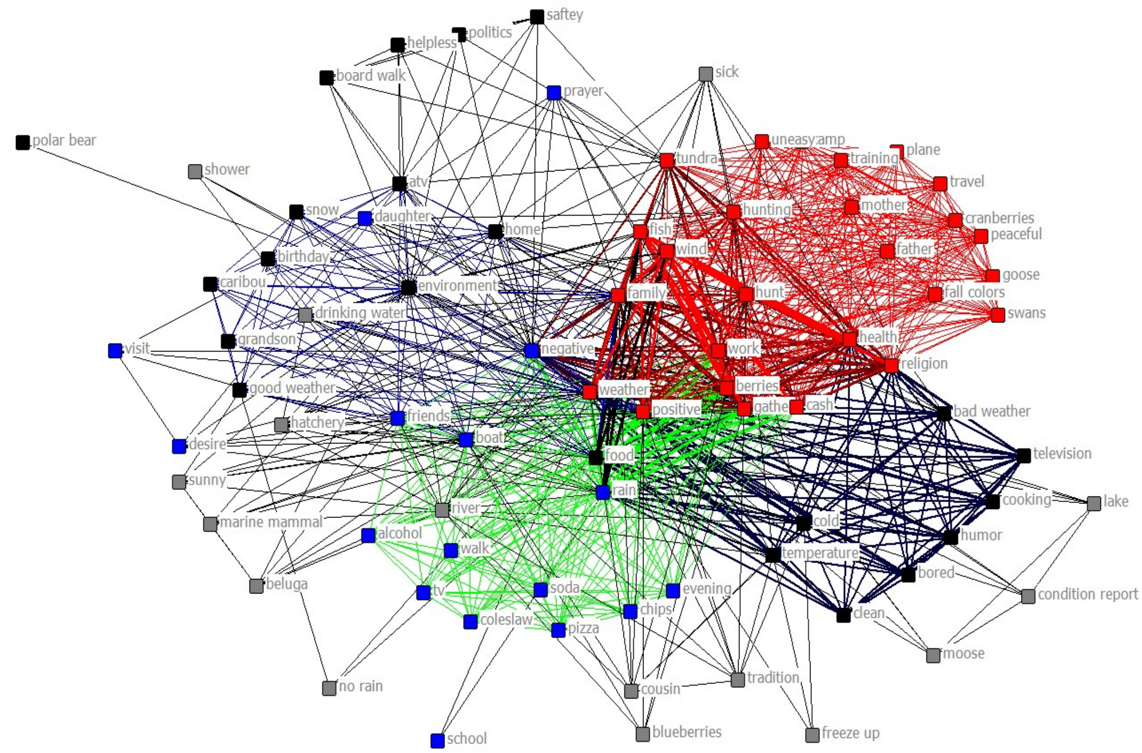

Figure 3.9 Community B Affiliation Network Before Freeze-up. Color of nodes represent faction membership. Tie colors are indicative of cliques' groupings.

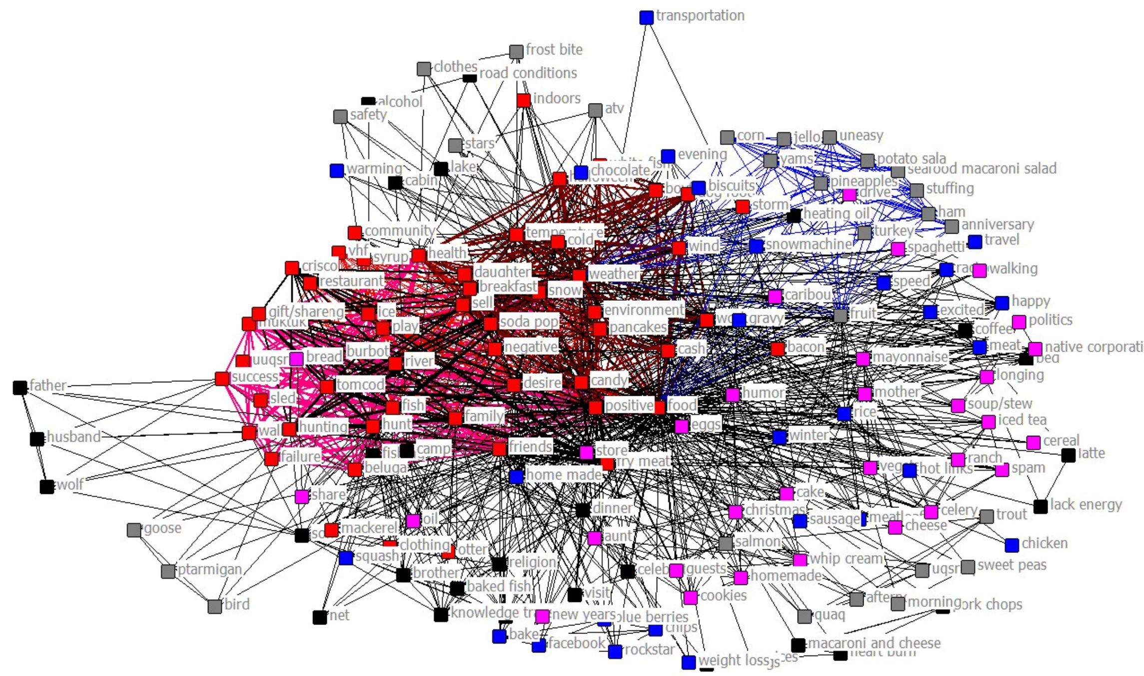

Figure 3.10 Community B Affiliation Network After Freeze-up. Color of nodes represent faction membership. Tie colors are indicative of cliques' groupings.

3.7 Tables

Table 3.1 Community A Content Analysis to Instrumental Observations.

Post #	Tmax	Tmin	Precip.Total	Wind Avg mph	Inductive
466	53	50	0.66	20.5	gather, rain, berries, drinking water, humor
473	45	39	0.05	12.7	rain, clouds, negative
475	51	40	1.49	23.3	rain, drinking water, humor, negative, bored, desire, berries
481	52	48	0.18	18.4	rain, flood, atv, roads
482	52	48	0.18	18.4	religion, humor, rain, drinking water
486	53	47	0.05	13.8	good weather, sunny, negative, rain
498	52	42	0.62	26.8	river, creek, flood, atv, rain, desire, negative
500	50	46	0.05	10.2	school , drinking water
502	47	41	0.44	24.2	homes, negative, wind, uneasy
512	48	42	0.28	15.7	religion, drinking water
516	44	29	T	8.3	good weather, humor
522	40	27	0.42	12.5	river, rain, humor
523	40	27	0.42	12.5	good weather, camp
541	34	30	T	25.6	brother, sister, family, religion, positive, temperature, cold, clothes, health
550	37	33	0.06	14.7	snow, coffee
563	31	11	0.07	7.9	snow, friends
564	31	11	0.07	7.9	snow, clothes, health, humor, positive
565	31	11	0.07	7.9	snow, positive,
570	31	28	0.03	24.5	snow, travel, plane, snowmachine
594	2	-8	0	6.9	cold, temperature, walk, humor
595	15	3	0	12.4	wind
596	15	3	0	12.4	wind
621	-6	-20	0	9.2	temperature
627	16	8	T	11.9	temperature

Table 3.2 Community A Centrality Rankings, Before and After Freeze-up

Degree Ranking	Before: Community A	After: Community A
1	weather	food
2	hunt	positive
3	environment	hunt
4	positive	fish
5	rain	environment
6	negative	weather
7	river	caribou
8	hunting	mother
9	camp	soup/stew
10	humor	snowmachine
11	drinking water	friends
12	boat	quaq
13	brother	family
14	caribou	eggs
15	desire	desire
16	religion	trout
17	family	rice
18	uncle	muktuk
19	bear	whale
20	good weather	pizza

Table 3.3 Community A Clique Sets Before Freeze-up

	Clique Set
1	Weather rain drinking water humor environment water system media river government homeland security positive flood ATV roads religion
2	Weather rain humor environment river positive hunt camp caribou good weather brother friends boat moose porcupine
3	Weather rain negative environment positive bear airport family son safety hunt uncle camp caribou Lack of fuel failure good weather sunny
4	Environment positive hunt uncle camp caribou food hunting brother friends boat cabin natural resource management document tradition

Table 3.4 Community A Clique Sets After Freeze-up

	Clique Set
1	Positive fish snowmachine food quaq muktuk mother community whale gingerbread daughter salted peanuts snack feast steak mayonnaise gather father ATV berries
2	Weather friends positive fish food trout quaq sister caribou muktuk soup/stew seal oil pizza temperature whale soda pop thanks gift chili dogs
3	Weather friends positive hunt fish food trout quaq caribou soup/stew seal oil soda pop
4	Weather positive hunt fish food trout food stamp store aunt candy soda pop river religion
5	Positive family food caribou soup/stew mother desire store macaroni and cheese vegetables corn son
6	Humor food eggs sausage french toast bread bacon fruit grilled cheese tomato soup apple Eggo celery holiday

Table 3.5 Community B Content Analysis to Instrumental Observations.

Post #	Tmax	Tmin	Precip. Total	Wind Avg. mph	Inductive
471	54	52	0.33	17.2	rain, school
474	47	40	0.03	12.8	good weather, no rain, positive
477	51	46	0.95	22.4	cold, positive, humor
478	51	46	0.95	22.4	negative, bad weather, health, religion
479	51	46	0.95	22.4	temperature, cold
480	51	46	0.95	22.4	food, rain, clean, cooking, television, bored, negative
484	55	49	0.11	17	sunny, positive
488	57	48	0.04	14.1	sunny, positive, boat
489	57	48	0.04	14.1	positive, sunny
492	48	43	0.01	20.7	drinking water, shower, negative
497	49	41	0	9.9	rain, negative, daughter, visit, desire
501	50	46	0.03	11.4	walk, rain, cash, work, negative
503	52	46	0.45	12.6	rain
513	48	45	0.28	19.6	rain, negative
519	43	36	0	7.3	gather, berries, cranberries, positive, swans, goose, positive
					tundra, fall colors, fish, health, peaceful, religion
520	43	36	0	7.3	uneasy, wind
521	43	36	0	7.3	travel, uneasy, wind, plane, work, training, cash
527	46	40	0.35	10.7	rain, negative
529	43	39	0	6.6	good weather, sunny
544	41	32	0	16.5	snow, good weather, positive
549	40	30	0	6.1	boat, desire, negative
551	38	32	0.02	8.1	bad weather, health, negative, sick, family
553	43	36	0.41	23.2	cold, temperature, river, boat, cousin
562	34	25	0	5.1	temperature, freeze up, cold
567	29	19	0	24.2	temperature, cold, family, friends
571	26	21	T	27.6	wind, temperature, cold
572	30	20	0	4.9	ice, health
575	30	22	0	11	positive, ice, skating, friends
577	32	23	0.02	7.9	snow
578	32	23	0.02	7.9	snow, desire, play
579	28	21	0	19.7	snow, positive, humor

Table 3.5 Continued

Post #	Tmax	Tmin	Precip. Total	Wind Avg. mph	Inductive
583	26	19	0	18.9	indoors, temperature, cold, health
584	22	14	0	15.2	Halloween, temperature, cold, health, positive
585	22	14	0	15.2	positive, work, cash, wind
597	-7	-16	0	6.3	snow, desire, positive
600	-7	-13	0	6.4	snow, desire, positive
601	-7	-13	0	6.4	snow, desire, positive
602	-10	-24	0	2.6	cold, temperature, health
604	-13	-19	T	16.5	cold, frost bite, health, temperature, clothes
606	2	-18	0.14	27.1	wind, cold, temperature
607	2	-18	0.14	27.1	snow, positive
608	2	-18	0.14	27.1	storm, humor
613	3	-6	0	30.2	wind, uneasy
632	23	18	0.02	16.4	temperature, warming, positive
634	23	18	0	17.1	snow, desire
635	23	18	0	17.1	snow, desire

Table 3.6 Community B Centrality Rankings, Before and After Freeze-up

Degree Ranking	Before: Community B	After: Community B
1	weather	food
2	positive	positive
3	negative	weather
4	rain	environment
5	environment	hunt
6	boat	friends
7	gather	desire
8	berries	temperature
9	family	cold
10	food	snow
11	hunt	health
12	river	humor
13	health	family
14	friends	fish
15	hunting	ice
16	temperature	hunting
17	cold	wind
18	home	negative
19	good weather	rice
20	sunny	work

Table 3.7 Community B Clique Sets Before Freeze-up.

	Clique Set
1	Weather positive health religion gather berries cash work hunt family hunting camp father mother cranberries swans goose tundra fall colors fish peaceful uneasy wind travel plane training
2	Weather positive negative health religion gather berries cash work hunt family hunting tundra
3	Weather good weather positive food environment boat friends family home ATV grandson birthday caribou snow
4	Weather rain positive health religion food gather berries cash work family fish wind
5	Weather rain positive humor negative bad weather health religion temperature cold food clean cooking television bored
6	Weather rain positive negative food boat friends gather berries pizza coleslaw chips soda evening alcohol TV walk cash work

Table 3.8 Community B Clique Sets After Freeze-up

	Clique Set
1	Environment ice food positive weather family friends hunt fish play pancakes syrup daughter negative restaurant sell vhf desire burbot river skating
2	Ice food positive weather friends hunt fish health burbot river beluga muktuk uuqsruq sled success failure walk
3	Food candy positive weather temperature cold wind health daughter sell work cash soda pop boyfriend white fish dog food Halloween
4	Food positive weather family hunt fish play sell desire river tomcod gift/share fry meat Crisco hunting snow
5	Food weather wind anniversary turkey stuffing ham pineapples seafood macaroni salad potato sala yams corn Jell-O fruit uneasy

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General Conclusion

Study Goals

In this thesis, I have attempted to outline a new methodology for incorporating social media data from the website Facebook into integrated SES-based research projects. I first locate this methodology within an academic framework that incorporates ideas from the research fields of communication, traditional knowledge, and resilience thinking. Next, I propose that SES scenarios can be developed from social media communication patterns utilizing this methodology. I then present a set of deductive-inductive content analysis procedures to define these patterns and take a network analysis approach to understand them from a systems perspective. This is done using two northwestern Alaskan communities as case studies to illustrate these points. Finally, I use these methods to explore Facebook communication patterns in relationship to instrumentally observed ecological conditions.

In placing my work in an academic framework, I introduce basic principles of network analysis and construct two-mode networks from the literature of each research field. Using these networks, I identify key structures and specific pieces of work for detailed content analysis. Based on the combined network and content analysis results, I then draw three primary conclusions about where my work fits into this larger reference frame of academic study, which are 1) my work supports current communication research exploring computer mediated identity presentation, 2) my work fits most closely with traditional knowledge research that is interested in the environmental information ingrained in this form of knowledge, and 3) my studies connect closely to resilience thinking efforts that attempt to address environmental change issues from a systems perspective.

It is important to realize that conclusions two and three above, are closely related, and that the deductive-inductive content analysis procedures I develop in the second, and third sections of this work are designed to bridge the inherently different worldviews held between these two ways of knowing. The communication field acts most accurately as the backdrop through which my work attempts to address traditional knowledge and resilience thinking issues.

Next, I focused on a method for using spatially grounded Facebook networks to detect local scale SESs. The first step in the method is to develop a researcher-defined framework of deductive code-phrases relevant to the SES of interest. This framework is used to filter raw, user-produced, Facebook content into study-specific themes. The focused content is then inductively coded into grounded code-phrases. These code-phrases are combined with the deductive phrases, as well as additional social-network data, to define relationships between social influence and the content themes expressed through the code-phrases. One and two-mode networks were used to analyze these relationships and conceptualize the types of system perspectives that can be developed using social media-derived data. The combined deductive-inductive analysis allows a form of translation between worldviews. However, it needs to be noted that the analysis will bias translation from the worldview captured by the inductive code to the institutional structures and perspectives represented in the deductive code.

This deductive-inductive methodology was tested using publicly available Facebook content from two rural Alaskan communities. Data was collected from August 2012 through January 2013. A deductive framework was built around concepts of the subsistence life-way, and the specific code-phrases (weather, hunt, gather, food, and environment) were developed based on my understanding of this system. Using the procedures outlined above, I develop a SES scenario useful as an example to illustrate the types of system interactions that can be explored using these methods. To be clear, the scenario I present is just one possible example that could be developed from this method. I believe the ability of this method to generate multiple scenarios is one of its strongest assets. Based on this feature, I propose that these methods are best used as a system scoping tool and deployed in conjunction with additional natural and social science methods. In addition, this tool is well situated to be used early on in the research process of larger, more comprehensive, SES investigations. Furthermore, it is an ideal tool to help quickly delineate potential system dynamics conducive to more focused efforts, as well as help define what methodologies, both from the social and natural science fields, may be the most appropriate to use.

Finally, I apply these deductive-inductive methods to explore Facebook communication networks in relationship to instrumentally defined environmental conditions. However, in order for social media derived data, specifically Facebook data, to be relevant to SES studies, a direct link must be tied between an environmental science understanding of the world and the types of information that can be gathered through social media channels. This link, made in the final chapter, compares the frequency and content of Facebook posting patterns to instrumental weather observations. I use the deductive-inductive methods described in chapter two to define a sample set of Facebook content and then compare it to average daily temperatures, precipitations, and wind speed for each of the two case-study communities.

I find that there are two main types of weather events that are easily identified in the Facebook communication patterns for these communities. These are 1) unusual, and/or 2) anticipated shifts in weather conditions. First, a persistent pattern of rainstorms through the early portions of the study is presented as an example of the types of unusual weather events that can register on social media networks. Second, freeze-up, the transition from liquid to solid water at a landscape level, is significant to the subsistence life-way and is presented as an example of anticipated weather events that are detectable through Facebook. In both cases, increased Facebook posting frequency and shifts in content relationships can be seen to align with instrumental records. These are presented as local system responses to weather changes. However, I do not claim that these types of events (unusual and/or anticipated) will be detectable in every social media derived system. For example, not all types of environmental conditions can be expected to register via social media. In the case studies I have explored here, large fluctuations in wind speed were instrumentally recorded but not noted via Facebook. This is likely because in this portion of Alaska, wind events of this type are expected and common, thus not socially noteworthy. Therefore, as a broader statement, it seems likely that only shifts in the expected environmental patterns are noted. The exception is expected dramatic changes that trigger regular, larger scale, social-ecological system transitions, like freeze-up.

I conclude that this positions Facebook-based research nicely to identify specific social and ecological component interactions that are 1) new, unusual, and/or upsetting to customary norms, and 2) are a consistent part of the anticipated SES and are important triggers to regular large social shifts within it. Many more case studies need to be explored to carefully define the types of social and ecological feedbacks that will, or will not, register through Facebook communication patterns.

Methodological Next Steps

I suggest two immediate next steps to advance the methodology I have developed in this thesis: 1) testing more systems, and 2) developing a participatory version.

To test more systems, the first step should be to apply the deductive framework and instrumental comparisons used here to a number of other spatially grounded Facebook communities in rural Alaska. This could provide a range of similar systems to test network consistency across sample sets. This type of comparison offers the additional benefit of being able to explore the links between regional SES cross scale relationships.

In addition to testing similar systems, fundamentally different system conceptualizations need to be tested to define the flexibility of the method. This should involve developing systems by changing the deductive framework. Diverse systems should also be defined, and tested, that are grounded in non-spatial concepts of communities, examples being hobby and/or professional communities. Lastly, while this study limited examination of real-world feedback to weather conditions, Facebook system results should be tested against a greater variety of real-world feedbacks. Both natural and social science measures should be used to examine these feedback mechanisms. Research exploring these themes will help to further establish the limitations and best uses of Facebook-based SES development.

After a variety of systems are tested, the development of a participatory version of the method is the next step. A main obstacle in doing this is simply identifying whom to participate with. An initial attempt might logically be expected to use general network centrality measures to define key players, and then attempt to build working relationships with the individual users identified. However, the difficulty is that different parts of the system are better understood by different participants within it. Participatory relationships are best built based on what system interactions are of most interest. So simple, whole-network, centrality measures cannot be used to define key players. Instead, centrality measures should be derived for individuals based on subgroup analysis of divisions within the larger network. Key players can then be identified for each subgroup and then tested by comparing network measures for the whole network against the same measures for the key player's ego network.

If there can be found a correlation between these networks, I believe data derived from key player communication patterns can then be used as a proxy for whole network activity. This is an important step to make because the size of these networks can produce unwieldy volumes of data, at least with respect to maintaining context through the inductive coding process. The ability to limit that data to workable levels, by monitoring key players, opens up the usefulness of the method to many more research settings.

Furthermore, participation directly with key players allows a number of different questions to be pursued that are not easily addressed purely through observation. In observation-based, Facebook derived SES development; a main limitation seems to be the ability to detect normal, everyday environmental interactions. Participatory methods that pursued identification of these types of routine events would add significant insight into system development efforts by being able to ask direct questions of the participants. Additionally, participatory methods can allow direct access to affect strategic change within a system.

I think this can help to avoid unintentional, negative system transitions as societies adapt to the new pressures of the anthropocene. In the predominantly indigenous communities of rural Alaska, these types of efforts must be approached with an extreme awareness of the region's history with Western colonization. Care must be taken that the power to define system issues and potential change outcomes is firmly held by system participants. Even in systems that don't share this colonial history, participatory methods that involve all relevant actors, or stakeholder groups, are an ethical requirement for any intentional efforts at system change. The methods I have presented in this thesis offer an excellent way to identify and draw in these various individuals and groups.

In short, the increasing adoption rates of social media, and specifically Facebook, by diverse populations globally, and the ability of the presented methods to translate between worldviews via the deductive-inductive coding process, well situates this work to address a wide variety of SES questions. As the methods are applied to a variety of systems, methodological refinements seem likely to further expand the types of system questions they can be adopted to assess. Importantly though, as the method is applied to more and more diverse systems, greater definition of the tool’s limitations will be possible as well. It's my hope that through efforts to expand its application, while clearly defining its limitations, this method can be applied at the practitioner level to community planning efforts, which aim to address real-world SES challenges.

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